What workers do and how

A European database of tasks indices

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This paper presents a new and enriched version of the JRC-Eurofound database of tasks indices across jobs in the EU15 economy. After a review of the existing measures and applications, we present the taxonomy of tasks which conceptually underlies the database. Next, the construction of the task indices is presented. We analyse the tasks profile of the European average worker, providing useful insights into work content and organisational methods, and how different indices are distributed across occupations. Finally, we show how the different types of tasks and work methods are correlated, which helps to understand how tasks are grouped within jobs.

L'articolo presenta una versione aggiornata del JRC-Eurofound tasks database a livello di job per l'EU15. Dopo una disamina delle misure e applicazioni esistenti, viene presentata la tassonomia dei tasks che sottende concettualmente il database e la costruzione degli indicatori che lo compongono. Successivamente, analizziamo il profilo dei tasks del lavoratore medio europeo, evidenziandone come diversi indicatori siano distribuiti tra le diverse occupazioni. Infine, mostriamo come contenuto dei tasks e metodi organizzativi siano correlati tra loro per comprendere come i tasks siano raggruppati all'interno dei posti di lavoro.

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Introduction[1]

Until not so long ago, economists paid little attention to the task content of jobs and occupations. The production process and the role played by labour in it have been handled in labour economics by the convenient black box of the production function, and in the analytical models, labour has been at best differentiated according to its potential productivity, proxied by skill level. But the empirical observation of a non-linear evolution of employment growth across skill levels in some advanced economies since the 1990s led some economists to search for a more nuanced understanding of how technology affected different types of labour inputs (Autor *et al.* 2003; Goos and Manning 2007). The hypothesis that computerisation has a "routine-biased" impact on employment (replacing routine jobs and

1 The present article builds on the JRC-Eurofound working paper Bisello M., Fana M., Fernández-Macías E., Torrejón Pérez S. (2021), *A comprehensive European database of tasks indices for socio-economic research*, Seville, European Commission. All main sections have been revised in the present article, while we refer and cite the working paper for technical annexes which have not been reported in the current version.

complementing non-routine ones) provided a starting point for this more nuanced understanding: labour input could be broken down into a series of distinct 'tasks', which could then be classified according to the specific types of skills they require.

Thus, a whole new literature has emerged in the field of labour economics in the last two decades, discussing how different types of task content were associated with different outcomes in terms of employment, wages or other dimensions related to job quality and working conditions, often in relation to the impact of technical change or international trade (for a review, see Eurofound 2016). While this literature has without any doubt enlarged the scope of economic research and improved our understanding of recent labour market trends, it suffers from some conceptual and empirical limitations that are worth mentioning. First, it ignores very rich traditions in other fields of social sciences of research on the division of labour, work organization and occupational change. For instance, in *Labor and Monopoly Capital* (1974), Braverman already spoke about a tendency of polarisation in the occupational structure, with declining employment for mid-skilled working-class occupations and expanding low-skilled service jobs[2]. Even within the economics discipline, theoretical contributions like the organizational theory of the firm and the capability theory of the firm (Cetrulo *et al.* 2020; Dosi *et al.* 2001; Dosi and Marengo 2015) discuss the implementation of organizational routines within firms as well their relationship with the creation and appropriation of knowledge over the occupational hierarchy. Secondly, most of the recent economic research on tasks has been based on classifying occupations rather than measuring task content as such (although this is changing in most recent years, as a result of better data availability). Third, most of the task-related economic research tends to focus on specific categories of task content (most frequently routine, manual and cognitive tasks), neglecting the fact that jobs are coherent bundles of interrelated tasks which cannot be properly understood in isolation. Fourth, the tasks approach adopted in labour economics is often grounded on a deterministic view of the process of substitution/complementarity between working activities (tasks) performed by human labour and by machines. In this approach, whether a given task is performed by humans or machines is fully determined by comparative advantages, disregarding social relations prevalent in a given historical and institutional context.

In 2016, Fernández-Macías *et al.* (2016b) developed a comprehensive hierarchical taxonomy of task contents (the JRC-Eurofound taxonomy of tasks, hereafter), methods and tools of work that tried to overcome some of these limitations. On the basis of this taxonomy and using existing data sources that included task-relevant information as well as comparable occupational classifications, a database of task indicators for occupations was created. These indicators followed rigorously the tree structure of the taxonomy, and thus could be aggregated at different levels and simultaneously analysed.

In this paper, we present a new version of this tasks database, embedding some important novelties compared to its predecessor. First, it is based on a revised version of the underlying taxonomy, which was published in 2022 (Fernández-Macías and Bisello 2022). Although this new version of the taxonomy remains broadly consistent with the previous one, it is sufficiently new as to require a new operationalisation, as presented in this paper. Second, since the first version of the tasks database was made public, new and better European data sources on tasks have been made available, allowing for the use of more updated and reliable data. More specifically, the construction of this new version of the JRC-Eurofound tasks database uses a more recent version of the European Working Conditions Survey (Eurofound 2016)[3] and the Italian version of the O*NET database of occupational contents. Only in the case of the OECD´s PIAAC Survey we use the same data source as in the first version of the database, although even in this case some indices have been updated to reflect the changes in the underlying taxonomy.

This paper unfolds as follows. Section 1 makes a review of the different measures recently used in differ-

2 It is interesting to note that Braverman also based these arguments on an analysis of long-term trends in employment across different occupational levels and discussed in detail the impact of technology on the task content of occupations. However, we should not take this argument too far: obviously, there are fundamental differences in the main arguments of the routinisation literature and Braverman´s work (Braverman 1974).

3 In 2021, Eurofound carried out a new round of fieldwork for the European Working Conditions Survey (EWCS). However, the available information on tasks is more limited than in the EWCS 2015. This is partly due to the change in interviewing mode (from face-to-face to computer-assisted telephone interviewing) which imposed restrictions on the questionnaire length, and the information to be collected.

ent fields of social sciences. Section 2 briefly presents the JRC-Eurofound taxonomy of tasks. In Section 3, a detailed presentation of sources and methodology adopted for the construction of the tasks indices is provided. In Section 4, we present the average distribution of tasks across European labour markets, while Section 5 discusses how tasks cluster across different occupations and sectors. The last Section concludes with some final remarks.

1. A review of existing tasks measures and their applications

In the last two decades, the increased attention paid to the role of tasks in shaping structural change in employment fostered the development of new and more granular and detailed data sources. As already stressed by Autor (2013), studying patterns in tasks within and across occupations is not feasible unless tasks data at the individual level are collected consistently at more than one point in time. Similarly, different economies are characterized by different economic processes depending on historical and institutional factors, and therefore using the mapping of tasks collected in a single country to inform on other economic structures may lead to biased estimates (Fana *et al.* 2020).

The rest of this Section briefly reviews the main types of data sources collected at the country and international level which have been used to operationalise the different classifications of tasks developed in the literature. It is worth highlighting that although the non-availability of data is detrimental to empirical applications, the theoretical grounds informing them is pivotal. For instance, the same source of data can be used in radically different conceptual frameworks, depending on what researchers are looking to operationalise.

Measures based on occupational databases

In their seminal work, Autor *et al.* (2003) made a systematic effort to classify occupations according to their intensity of use of some specific types of tasks, namely *nonroutine analytic, nonroutine interactive, routine cognitive, routine manual* and *nonroutine manual*. The resulting classification[4] was operationalised using the Dictionary of Occupational Titles (DOT), an occupational database that contains detailed descriptions of occupational contents made by trained job analysts based on their observations and interviews at selected job sites for the US economy. In the DOT, experts evaluated the importance of many different task and skill categories across different detailed occupations, assigning standardised scores to each item.

Other researchers replicated the ALM (Autor, Levy and Murnane) model or produced reformulations, introducing adjustments to adapt their data to their specific interests, while still using DOT or its successor the *Occupational Information Network Database*, known as O*NET. Cunningham and Mohr (2019) add the type of tools used at work and, more generally, the tasks that are associated with a higher and a lower pay (job specific tools and general tools) to the original ALM indices. Blinder (2009), to proxy the risk of displacement because of international trade, created an index of jobs offshoreability based on the requirement of physical location and proximity to the work unit. More recently, direct contact and physical proximity have been used by Dingel and Neiman (2020) to study the potential for telework during the Covid-19 pandemic[5]. More in line with the original proposal, the ALM taxonomy (with refinements in some cases) built using DOT/O*NET occupational content data has been matched with employment data to illustrate changes in the work composition of several European (Acemoglu and Autor 2011; Arias *et al*. 2014; Goos *et al*. 2014; Goos and Manning 2007; Górka *et al*. 2017; Hardy *et al*. 2018) and non-European countries (Sarkar and Torrejón Pérez 2023). Similarly, Arias *et al*. (2014) use measures of skill requirements, defined following the ALM model, and extrapolate these measures to the occupational structure of countries in Central and Eastern Europe and Central Asia.

While DOT and O*NET contain U.S. data, the *Indagine Campionaria sulle Professioni* (ICP), developed by the National Institute for Public Policy Analysis (INAPP) and the Italian National Statistical Institute (ISTAT), constitutes the only European data source closely replicating O*NET for the Italian occupational structure. This Italian version of the O*NET has been extensively used in recent years. Cirillo *et al*. (2021) adopt the standard ALM task approach to investigate the routine bias hypothesis in the Italian context, finding supporting evidence. Another contribution which uses ICP is Cetrulo *et al*. (2020). Departing from the standard approach,

4 Other indices to measure the intensity of routine tasks at work have been developed by Autor and Dorn (2013), Autor *et al*. (2015), Goos *et al*. (2014), Verdugo and Allègre (2020) ecc.

5 See Sostero *et al*. (forthcoming) for an application of the tasks framework used in this paper to the analysis of teleworkability.

the authors put human agency and organizations at the centre of the stage, highlighting the importance of power relations, hierarchies and knowledge as the most relevant attributes characterizing the division of labour.

The main advantage of occupational databases such as DOT, O*NET and the ICP is that they cover the entire spectrum of the occupational structure at a high level of detail. These sources are the most comprehensive databases reporting information on tasks, skills, work contexts, and to a lesser extent organizational characteristics. But they have important limitations too. First, they provide information at the level of occupations rather than individual workers, not accounting for the variability of tasks within the same occupation. For the same reason, since task differences between economic sectors are not captured, the horizontal dimension of the division of labour is entirely missing. Second, in the case of O*NET, it gathers data from professional job analysts, and from 'occupational experts' on small occupations that are difficult to reach through sample (Freeman *et al*. 2020, 3). ICP instead is based on survey evidence collected at the worker's level, validated ex-post by experts. Third, these sources were not originally constructed to measure changes in the task content over time, but rather to have a detailed measure of occupational content at a specific point in time. To our knowledge prior research has used O*NET data mostly cross-sectionally, with only a couple of exceptions (see Freeman *et al*. 2020; Ross 2017).

Measures based on survey data

A second empirical approach to task measurement is based on survey data in which respondents indicate the type of activities they perform on their job. This type of data offers some advantages. First, provided the sample size is large enough, the resulting databases allow us to analyse the variability of tasks indices within and between jobs, defined either at the detailed occupational level or for each occupation by sector pair. Second, these sources are better suited to capture changes in task contents, as long as they actually occur. Third, they allow the creation of new task measures that can be used for testing specific hypotheses. Furthermore, surveys usually include additional information which complement activities performed at work with workers' individual characteristics, such as education and experience, or other attributes of their jobs, such as wages or the type of contract. In summary, the potential applications of the task approach to labour market analysis are increased considerably by making use of survey data.

A widely used data source is the Qualification and Career Survey, a survey of employees carried out by the German Federal Institute for Vocational Training (BIBB) and the Research Institute of the Federal Employment Service (IAB), that offers detailed self-reported data on workers' primary activities at their jobs. The survey is carried out every six years, the last one in 2018. The datas*et al*so includes detailed information on the tools and machines used at the workplace. Based on these variables, Spitz-Oener (2006) elaborated indicators that reproduced the categories of the ALM model, adding information on computer use. Others have used the IAB/ BIBB data to explore links between technological change, the composition of employment and shifts in wage structure (Antonczyk *et al.* 2010; Dustmann *et al.* 2009; Senftleben-König and Wielandt 2014).

In 2014, a new survey was developed by IAB to operationalize five major types of tasks: analytic, interactive, manual, routine, and autonomy-demanding ones. The resulting questionnaire was administered in the fourth panel wave of the German National Educational Panel Study's (NEPS) adult stage. Matthes *et al*. (2014) use this data to operationalise an extended version of the ALM taxonomy in which routine tasks are defined over two main dimensions (task complexity and lack of autonomy).

Another workers' survey covering a European country is the French *Enquête Complémentaire Emploi: Conditions de travail* (EC hereafter) developed since 1978 by the Direction de l'Animation de la Recherche, des Études et des Statistiques of the French Ministry of Labour. The EC is representative of the entire working population by occupation and sector at a high detailed level. It collects information at worker level on tasks performed, organisational methods, socio-demographic characteristics, contractual arrangements, and wages. The main building blocks and questions of the EC have been maintained almost unaltered, allowing for dynamic analysis of tasks and organizational methods. The richness of the survey allows to cover a wide range of tasks indicators which have been used to investigate, among other things, the relationship between innovation and working conditions (Greenana and Mairesse 2000), gender differences in power and control (Fana and Giangregorio 2023) and the impact of outsourcing on wages and working conditions (Lizé 2021; Fana *et al*. 2022).

Michael J. Handel created the Skills, Technology, and Management Practices (STAMP) survey, explicitly designed to overcome the limitations of the O*NET by capturing tasks at the worker level. The survey contains approximately 166 unique items on job characteristics, covering skills and task requirements in terms of a detailed list of intellectual activities (reading, mathematics, problem-solving, visuals) and a broader category for physical tasks required at work. It also includes ICT and non-ICT technology; employee involvement practices; autonomy, supervision and authority (Handel 2008; 2016). The STAMP questions were subsequently revised, leading to the Princeton Data Improvement Initiative (PDII) led by Alan Krueger, Ed Freeland and Bill Barron, and conducted only in 2008, reducing the scope for dynamic analysis. Also, this survey has been used to refine the ALM to include physical tasks, repetitive tasks, managing/supervising, problem solving, and math (Autor and Handel 2013). Blinder and Krueger (2013) and Goos *et al*. (2014) have also used the PDII to generate an index to measure the offshorability of jobs.

The OECD Survey of Adult Skills (PIAAC) measures adults' proficiency in key information-processing skills (literacy, numeracy and problem solving), and gathers information on how adults use their skills at work and in the wider community. This survey is conducted in over 40 countries. For that reason, it has been widely used to produce indices aimed at measuring the skill and the task content of work (De La Rica *et al*. 2020; Górka *et al*. 2017; Martínez-Matute and Villanueva 2020; Nedelkoska and Quintini 2018; OECD 2016; Vignoles and Cherry 2020).

In Europe, one of the most important sources on work and tasks is the European Working Conditions Survey (EWCS). Developed by Eurofound, it was launched in 1990, and aimed at providing an overview of working conditions in Europe. This survey is conducted every five years[6] and contains information about the everyday reality and the activities of men and women at work. Joling and Kraan (2008) and Salvatori *et al*. (2018) propose an indicator of machine use at work based on the EWCS to study the association between technology use and job quality. Sebastian (2018) investigates the main determinants behind job polarisation in Spain between 1994 and 2014. Using this database, the author analyses employment changes of different jobs, classified on the basis of their task content as abstract, routine, and manual (similar to the standard ALM model). Bisello *et al*. (2023) also rely on this source to analyse changes in the task content, methods and tools of European jobs from 1995 to 2015, drawing on the taxonomy of tasks proposed by Fernández-Macías *et al*. (2016a; 2016b). In a similar fashion, Gil-Hernández *et al*. (2023) rely on the EWCS to investigate the task distribution between social classes, and how job tasks might blur the links between employment relations, classes and life chances. Finally, the EWCS data were used, together with other sources, to estimate the potential of working from home, based on the task content of work (Sostero *et al*. 2023).

Finally, the European skills and jobs survey (ESJS) is another EU-wide survey aimed at collecting information on the skill requirements, skill mismatches and initial and continuing learning of adult workers in EU labour markets. Developed by European Centre for the Development of Vocational Training (Cedefop), the first wave of the ESJS was carried out in 2014 while its second one in 2021. This database has been used to identify the risk of automation in European labour markets based on job tasks (Pouliakas 2018) and to research skill mismatch in labour markets (see Polachek *et al*. 2017 for a selected number of peer-reviewed academic studies). More recently, the ESJS was also used to investigate the potential of working from home in Greece (Pouliakas 2020), as well as the employment effect of Covid-19 social distancing restrictions (Pouliakas and Branka 2020).

Measures based on online vacancy data

Finally, there is a new type of data source that has been recently used to construct indicators on tasks. In recent years, the Internet has become the dominant medium for advertising job vacancies. Advances in machine learning and cloud computing have allowed to translate the massive amounts of unstructured qualitative data present in online job ads into usable databases containing detailed information on the characteristics and requirements of the jobs advertised. Since online job ads typically incorporate detailed descriptions of the skills required and even the nature of the job to be fulfilled, and since they are generally classified by a detailed occupational title, they can be also used to construct detailed indicators on tasks across occupations.

In a recent paper, Sostero and Fernández-Macías

6 The fieldwork for the last wave, due to take place in 2020, was postponed due to the Covid-19 crisis. The EWCS 2021 extraordinary edition was later conducted as telephone survey in 36 countries.

(2021) use the JRC-Eurofound taxonomy of tasks to create indicators of task content, methods and tools, systematically comparing the results obtained from online job ads with the results obtained from the database presented in this paper. They find that the task profiles implied in job advertisements are relatively consistent with the JRC-Eurofound tasks database across most occupations, especially for intellectual and social tasks, and for tools of work. However, they also find that online job advertisements in general tend to focus on professional occupations, which are relatively better represented in their numbers and in their variety of skills and tasks, than less qualified occupations. Pouliakas (2021) uses online job ad data to construct task profiles of detailed occupations to predict the risk of automation, finding that work activities associated with greater occupational automation risk and robot exposure (e.g., inspecting equipment, performing physical activities), typically concentrated in routine or manual jobs, differ from those prominent in occupations with higher AI exposure (e.g. thinking creatively, evaluating standards).

2. The content of work, the methods and the tools used in the workplace: a taxonomy of tasks

The taxonomy which underlies our database, presented in Table 1 below and discussed in detail in Fernández-Macías and Bisello (2022), was constructed in two steps. First, a detailed review of the recent empirical Social Sciences literature that referred to the concept of tasks was made to create an inventory of the types of tasks discussed. For instance, the literature on the impact of technology on employment tends to focus on two main types of tasks (cognitive and routine), although other types are sometimes mentioned (interactive, service and manual, for instance); while the literature on trade often focuses on social interaction tasks to capture the offshorability character of them etc. Secondly, a material and organisational model of work was developed to provide a conceptual structure to the mentioned inventory of tasks, and to identify and fill gaps where necessary. The result is the hierarchical taxonomy of tasks presented in Table 1.

The first dimension of the taxonomy refers to the *contents* of tasks. This dimension looks at work from a material perspective, as a transformative activity upon an object, tasks being discrete units of that work. Hence, on the basis of the type of object being transformed, there is a first threefold differentiation between *physical tasks* (operated upon objects), *intellectual tasks* (operated upon ideas or information) and *social tasks* (operated upon social relations). Within each of those upper-level categories of task contents, there are additional nested classifications based on the type of transformation and the skills typically required to perform them. For instance, intellectual tasks are first differentiated into information processing and problem solving. Information processing is then further differentiated into the processing of uncodified (visual or auditory) information, and the processing of codified information. Then, the processing of codified information is further differentiated into literacy (processing of textual information) and numeracy (processing of numeric information). And finally, literacy is further subdivided into business, technical and humanities. Therefore, this particular branch of the taxonomy has 6 levels (from task contents to the processing of technical textual information). The taxonomy is therefore hierarchical although not symmetric in its depth (some branches are more differentiated than others), and the different branches can be compared at equivalent levels (so 'strength' in physical tasks has a similar level of generality as 'information processing' in intellectual tasks or 'caring' in social tasks).

The second dimension refers to the *methods and tools* of work. Whereas the task contents dimension reflects directly the material properties of the work process (the type of object being transformed and the type of transformation operated upon it), the methods and tools dimension reflects the socially determined forms of work organisation and the technologies used in production. In terms of work methods (or forms of work organisation), three main categories are identified: autonomy, teamwork and routine. In terms of tools (or technologies used at work), a differentiation between analog and digital machinery is made. As in the case of task content, most of the upper-level branches of the taxonomy are further distinguished at different levels.

3. Creating the JRC-Eurofound tasks database

Data sources

Despite the interest in tasks performed by workers and the use of the tasks approach to explain structural change in labour markets, data availability remains poor, with some exceptions. At present there is no data covering all items included in the taxonomy of tasks at the European level, nor at the national level. However, international, European and national surveys do exist, providing a *partial* coverage of the taxonomy

Table 1. A taxonomy of tasks according to the content of work, methods and tools

A. In terms of the content:	**B. In terms of the methods and tools of work:**
1. Physical tasks: aimed at the physical manipulation and transformation of material things:	**1. Methods: forms of work organisation used in performing the tasks:**
a. *Strength:* lifting people and heavy loads, exercising strength	a. *Autonomy*
b. *Dexterity:* precisely coordinated movements with hands or fingers	I. Latitude: ability to decide working time, task order, methods and speed
c. *Navigation:* moving objects or oneself in unstructured or changing spaces	II. Control (in reverse): direct control by boss or clients, monitoring of work
	b. *Teamwork:* extent to which the worker has to collaborate and coordinate her actions with other workers
2. Intellectual tasks: aimed at the manipulation and transformation of information and the active resolution of problems:	c. *Routine*
a. *Information processing:*	I. Repetitiveness: extent to which the worker has to repeat the same procedures
I. Visual and/or auditory processing of uncodified/ unstructured information	II. Standardisation: extent to which work procedures and outputs are predefined and encoded in a formalised system
II. Processing of codified information	III. Uncertainty (in reverse): extent to which the worker needs to respond to unforeseen situations
i. Literacy:	
a. Business: read or write letters, memos, invoices,...	**2. Tools: type of technology used at work:**
b. Technical: read or write manuals, instructions, reports, forms,...	a. *Non-digital machinery (analog)*
c. Humanities: read or write articles or books	b. *Digitally-enabled machinery*
ii. Numeracy:	I. Autonomous (robots)
a. Accounting: calculate prices, fractions, use calculators,...	II. Non-autonomous
b. Analytic: prepare charts, use formulas or advanced maths	1. Computing devices
b. *Problem solving:*	a. Basic ICT (generic office applications)
I. Information gathering and evaluation	b. Advanced ICT (programming, admin)
i. Information search and retrieval	c. Specialised ICT
ii. Conceptualization, learning and abstraction	2. Others
II. Creativity and resolution	
i. Creativity	
ii. Planning/implementation	
3. Social tasks: whose primary aim is the interaction with other people:	
a. *Serving/attending:* responding directly to demands from public or customers	
b. *Teaching/training/coaching:* impart knowledge or instruct others	
c. *Selling/influencing:* induce others to do or buy something, negotiate	
d. *Managing/coordinating:* coordinate or supervise the behaviour of colleagues	
e. *Caring:* provide for the welfare needs of others	

Source: Fernández-Macías and Bisello (2022) which have been recently used to build a cross-country comparable database (Fana *et al*. 2020). In this paper, in order to operationalise the broad spectrum of items included in the taxonomy of tasks proposed by Fernández-Macías and Bisello (2022), different indicators from three different surveys are combined. First, we have used the sixth wave of the EWCS, carried out by Eurofound in 2015 covering nearly 44,000 workers in 35 countries. Its findings provide detailed information on a broad range of issues, including exposure to physical and psychosocial risks, work organisation, work-life balance, and health and well-being. Second, we have used the ICP, which covers the whole spectrum of the Italian 5-digit occupations excluding armed forces. The interviews are administered to 16,000 Italian workers, ensuring representativeness with respect to sector, occupation, firm size and geographical domain (macro-regions)[7]. In the present paper, information from the ICP is drawn from the 2012 wave and the intensity scale (ranging between 0 and 100) is used for all variables. Finally, we have complemented the previous two sources with the First Cycle of PIAAC (OECD) collecting data from 2011 and 2018 related to the proficiency of adults aged 15-65 in key information-processing skills-literacy, numeracy and problem solving. Apart from measuring the key cognitive and workplace skills, the survey also collects information on demographic characteristics, qualifications, work experience, training and use of skills at work, at home and in the community.

As explained in Section 1, both workers' surveys (EWCS and PIAAC) and occupational databases (ICP) have advantages and limitations. Although these limitations cannot be ignored, the availability of larger sample sizes in surveys and the possibility of combining multiple questions and sources for the construction of single items mitigates the risk of biased or inconsistent outcomes.

In order to combine the three sources, and to maintain a certain degree of consistency, the sample was restricted to the EU-15 countries, therefore using both EWCS and PIAAC[8] information only for those countries. This choice has led to the creation of task measures which primarily refer to Western European countries.

The sources used for the construction of indices for each category of tasks vary depending on the information available. Some elements are only covered by one of the sources, while in most cases the indices have been constructed by combining information from two or three sources. Even for the elements that are only covered by one source we have constructed the corresponding indices by using several variables from the same source[9]. As most of the variables used are just partial proxies of the concepts of the proposed taxonomy, this redundancy can increase the consistency and robustness of the measure, and make it easier to verify the validity of the underlying taxonomy.

Methodology

In order to construct the tasks indices from the mentioned sources, and following the same approach as Fernández-Macías *et al*. (2016b) the following procedure was adopted:

1. For each index, all the potential variables that could match the elements of the taxonomy were identified.
2. Given the variable or set of variables related to a specific indicator that were selected, three main statistical tests (pairwise correlations, Cronbach's Alpha tests, and Principal Component Factor Analysis) were performed to analyse the correlation and consistency among them. It is important to note that, in principle, variables aimed at measuring the same concept should be highly correlated, although this may not be the case if two variables capture complementary aspects of the same concept or if those variables, while capturing the same concept, are occupation-specific.
3. The variables selected to be combined into a single index were standardised into a 0-1 when necessary. Then, the selected variables were combined by simply averaging them at each relevant level.
4. Fourth, the construction of the indices from each source was followed by the computation

7 Since the unit of analysis is the five-digit occupation rather than the individual worker, standard deviations for the tasks indicators were not created as they would have reflected variability between occupations belonging to the same broad three-digit group, in contrast with the other two sources using individual data.

8 The sample of EU-15 countries that is available in PIAAC 1st round is formed by Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Spain and Sweden.

9 For the complete lists of sources and variables used for the construction of each indicator see Bisello *et al.* (2021).

of their average scores for all the occupation-by-sector combinations (in other words, for each 'job' in our terminology) at the two-digit level, using ISCO08 for occupation and NACE Rev.2 for sector; and for 2-digit occupations (ISCO08) in the case of ICP starting from the three digits of the original database.

While the aggregation of individual variables was performed using the most detailed level possible, the construction of indices at higher levels was carried out by simply averaging the indices below as indicated by the nested structure. This ensures that the values of the indices at higher levels are consistent with the lower ones.

Once the set of possible indices from each source had been created, information from the three sources was combined by appending the three databases[10]; next, weighted average tasks scores for all jobs were computed merging the complete database with employment data from an ad-hoc extraction of European Labour Force Survey (EU-LFS) 2019 at the EU-15 (minus UK) level provided at ISCO08 two digit and NACE Rev.2 at the same level of detail.

4. What Europeans do: the distribution of employment from a task perspective

The methodology adopted in the previous Section makes it possible to translate the taxonomy of tasks presented in Section 2 into a comprehensive task database at the EU-15.

To begin with the aggregate picture, Figure 1 shows summary statistics, including the average task scores for all workers in all jobs in the EU-15 and information about the dispersion of values around the mean. This figure was constructed averaging each task score across all jobs weighted by their employment level in the EU-15 (minus UK) in 2019. Using this calendar year enables us to characterise the European employment structure without being affected by compositional changes due to Covid-19 and the subsequent supply chain and energy crisis.

Figure 1 can be interpreted as an approximation of the task profile of the average worker in Europe. In terms of job content, the most frequent type of tasks in European employment is intellectual (in particular, problem-solving tasks), whereas physical tasks have a much lower prevalence and social tasks are somewhere in between. The dispersion of values around the mean and their distribution also varies significantly across task categories. Some problem-solving tasks (conceptualization, learning and abstraction and creativity), autonomy, teamwork and standardisation have high scores and a low dispersion and are thus very prevalent among European workers. On the other hand, business and humanities literacy and information search and retrieval have high scores but high dispersion, suggesting a more polarised distribution.

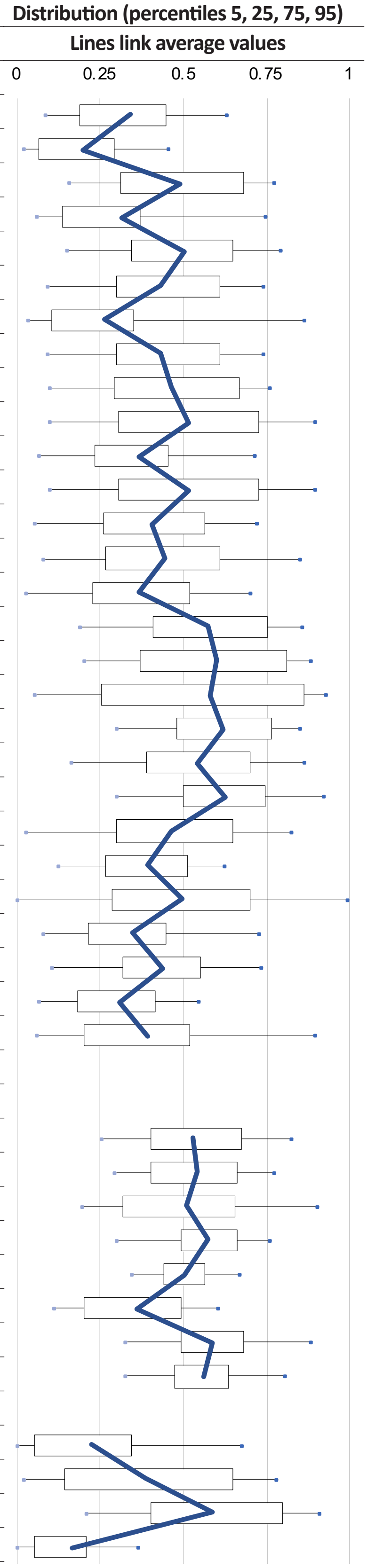
Among the three subdimensions of physical tasks, dexterity has the highest prevalence, while strength has the lowest one. As expected, when exploring the distribution of physical dexterity by occupation, it emerges that highest scores are found for market-oriented foresters, fishers and hunting workers, as well as metal, machinery and related trades workers, but also health (associated) professionals.

Intellectual tasks exhibit overall high average values, compared to physical and social ones, suggesting that most of European workers perform some intellectual tasks in the execution of their duties at work. However, it is more likely that a worker will be engaged in problem solving activities rather than in the processing of codified information (whether literacy or numeracy related). This finding should not come as a surprise if information processing is interpreted as the use of explicit knowledge for specific work activities, while problem solving involves both explicit and tacit knowledge. According to this interpretation, the processing of codified information, like reading/writing, whether for general and/or specialised purposes, characterises the job of fewer workers who are more likely to belong to the middle and upper end of the occupational distribution (from managers to clerks). On the contrary, activities involving conceptualisation/learning and creativity (even if they are not embedded into formalised activities) are more widespread across occupations. From the conceptual standpoint, this evidence is in line with recent studies on content of work and labour (Pfeiffer 2018) according to which tacit knowledge plays a crucial role in the performance of tasks, as well as workers capability to react to unforeseen situations. This interpretation finds preliminary confirmation in the summary statis-

10 Before averaging scores across the three sources, a new round of consistency tests by means of correlation, principal component factor analysis and Cronbach's Alpha test has been performed to check whether, within and between sources, variables consistently capture the same concept and task dimension. See full results in Bisello *et al.* (2021).

Figure 1. Average task scores for EU-15, 2019

Task indices	Summary statistics		
In terms of the content of work:	**Mean**	**Std dev**	**CV**
1. Physical	0.34	0.17	0.51
a. Strength	0.20	0.14	0.70
b. Dexterity	0.49	0.21	0.43
c. Navigation	0.32	0.20	0.64
2. Intellectual	0.50	0.19	0.39
a. Information processing	0.44	0.20	0.45
I. Visual and/or auditory processing of uncodified/unstructured info	0.26	0.21	0.82
II. Processing of codified information	0.44	0.20	0.45
i. Literacy	0.47	0.21	0.45
a. Business	0.52	0.25	0.49
b. Technical	0.37	0.17	0.47
c. Humanities	0.52	0.25	0.49
ii. Numeracy	0.41	0.20	0.49
a. Accounting	0.45	0.23	0.52
b. Analytic	0.36	0.20	0.54
b. Problem solving	0.57	0.21	0.37
I. Information gathering & evaluation	0.60	0.24	0.39
i. Information search and retrieval	0.58	0.31	0.54
ii.Conceptualization, learning and abstraction	0.62	0.18	0.29
II. Creativity and resolution	0.54	0.21	0.39
i. Creativity	0.62	0.18	0.29
ii. Planning	0.47	0.25	0.54
3. Social	0.40	0.15	0.39
a. Serving/ attending	0.50	0.27	0.53
b. Teaching/ trainin/ coachig	0.35	0.19	0.56
c. Selling/ influencing	0.44	0.19	0.42
d. Managing/ coordinating	0.31	0.16	0.50
e. Caring	0.39	0.25	0.63
In terms of the methods and the tools of work			
1. Methods			
a. Autonomy	0.53	0.19	0.35
I. Latitude	0.54	0.16	0.29
II. Control (in reverse)	0.51	0.23	0.45
b. Teamwork	0.57	0.14	0.25
c. Routine	0.50	0.10	0.20
I. Repetitiveness	0.36	0.16	0.46
II. Standardization	0.59	0.17	0.28
III. Uncertainty (in reverse)	0.56	0.15	0.26
2. Tools			
a. Non-digital machinery (analog)	0.22	0.22	0.99
1. Computing devices	0.39	0.26	0.67
a. Basic ICT	0.59	0.23	0.39
b. Advanced ICT	0.16	0.15	0.88



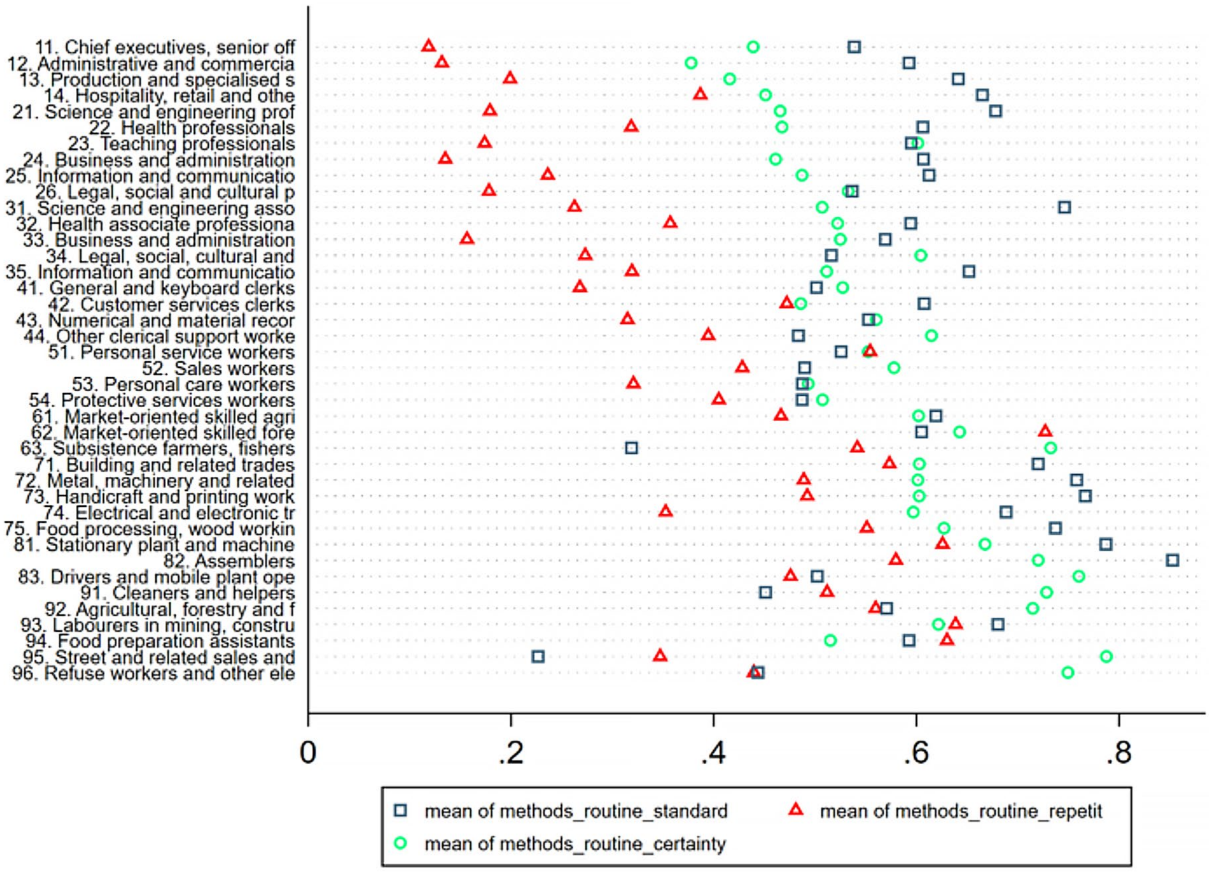
Note: employment shares in each job derived from the European Labour Force Survey 2019 data were used for weighting the indices.
Source: Authors' elaboration on JRC-Eurofound tasks database

tics reported in Figure 1, according to which information gathering and evaluation, and creativity and resolution, show high average values but low dispersion, while the relative dispersion for literacy and numeracy is higher.

Serving/attending is the type of social task that is more common in European employment, while managing/coordinating is the least frequent. The structural shift from the goods-producing sector (agriculture, construction and manufacturing) to service activities (Torrejón Pérez *et al.* 2023) partly explains the relatively high frequency of social tasks in European employment (apart from managing and coordinating, which mostly reflect hierarchical power). An extreme example is provided by sales workers (the occupation with highest values for serving/ attending), counting 10,5 million workers in 2019. But hospitality, retail and other services managers, health professionals, customer services clerks, personal service workers and street and related sales and service workers also involve much social interaction. In line with expectations, managing and coordinating activities are on average less frequent, reflecting the concentration of hierarchical power within organisations.

In terms of the methods of work, aggregate figures feature relatively high levels of autonomy and teamwork, but also some routine (in particular, with respect to work standardisation). Teamwork and, more markedly, autonomy display a higher dispersion compared to routine indicators, suggesting a more polarised distribution for the first two tasks. High scores of autonomy mostly characterise managerial and professional occupations, and to a lower extent electrical and electronic trades worker but also handicraft and printing workers and market-oriented agricultural workers. From a qualitative point of view, autonomy for managers is different than for electricians: indeed, the latter are relatively more often self-employed or micro-entrepreneurs bearing mainly external control, from clients or customers. Managers or chief executives, instead, enjoy great autonomy within a more complex organisation. On the other hand, our evidence is in line with evidence presented in the European Jobs Monitor 2016 (Eurofound 2016), according to which tasks are characterized by

Figure 2. Distribution of standardisation, repetitiveness and uncertainty (in reverse) by ISCO08 two-digit



Source: Authors' elaboration on JRC-Eurofound tasks database

relatively high levels of standardisation along the entire occupational distribution. Yet, standardisation does not necessarily imply high levels of repetitiveness, as shown by the contrasting values of some professional occupations. In short, while repetitive activities usually imply high levels of standardisation (as in the case of stationary plant and machine operators), the opposite is not necessarily true (see for instance science and engineering associate professionals). Finally, uncertainty (in reverse) also shows high levels on average and is spread across occupations. As it can be appreciated from Figure 2, certainty is higher for managers as well as assemblers and machine operators, while it is lower for sale workers and several occupations related to clerical activities. This finding supports the idea that even within highly repetitive and/or standardized work processes, tacit knowledge and problem-solving play a significant role (Pfeiffer and Suphan 2015). This peculiar distribution of indicators measuring routineness across occupations result in an overall indicator with low variability. As already discussed, this outcome is not a weakness of our measure but rather the consequence of the different ways in which standardisation, uncertainty and repetitiveness behave across different occupations.

Finally, in terms of the tools used at work, computing devices and in particular basic ICT are much more frequent than analog machines but also than advanced ICT tools, which is not surprising. High scores of basic ICT mostly characterise managerial and professional occupations and clerks, and to a lower extent protective service workers and electrical and electronic trades workers. Moreover our results, in line with the recent literature, point towards a positive association between standardisation and ICT (Bisello *et al.* 2023). This is the case for different categories within the Technical and Associate professionals' group as well as for Numerical and material recording clerks. At the same time, these are occupations showing higher levels of intellectual tasks. The relationship between basic ICT deployment, content and methods of work is less straightforward. Intellectual tasks of relatively high complexity can be simultaneously complementary to information technologies and standardised practices, and therefore routine. Another interesting result refers to the relationship between the use of ICT tools and social tasks. While high levels of managing and coordinating are associated with high level of ICT use, the opposite does not hold, suggesting that the concentration of managerial power is unrelated to technological complementarities.

5. How tasks correlate within jobs

One of the key advantages of using a detailed and comprehensive taxonomy rather than a general and fragmentary approach to task analysis is that it allows to evaluate thoroughly how different types of task content, methods and tools interact with each other. Task interactions can be as important for characterising jobs as the individual task scores themselves, so they merit specific analysis.

Table 2 shows the bivariate correlations between all the indices in the taxonomy, at all levels. This allows to evaluate associations among indices after the aggregation of all the three sources into final indicators.

Relationship within domains of task content

The table shows that physical and intellectual tasks are quite consistent internally. In the case of physical tasks, which have three components, the highest correlation is between tasks that require high levels of physical exertion and stamina (referred to in the index as 'strength') and manual dexterity (0.81). Somewhat lower positive correlations, but still above 0.6, are found instead for the index of navigation, that captures tasks of a slightly different nature, such as moving objects or oneself in unstructured or changing environments.

The much more detailed set of indicators of intellectual tasks also show quite high levels of consistency, with most bivariate correlations above 0.6. The notable exception is visual and/or auditory processing of uncodified/unstructured information, which consistently displays negative correlations with all the other indices in the intellectual domain. Social task content, on the other hand, is less internally consistent, except in the categories of managing/coordinating and teaching/coaching or selling/influencing, which often coexist in the same jobs (correlations above 0.7 in the case of both combinations). The tasks of serving and attending are meaningfully related only with selling/influencing, while they display much lower correlations with other social tasks. Finally, caring is certainly the most unique type of social work activity: indeed, providing for the welfare needs of others is a stand-alone task that is not often combined with others. Consequently, even though all the categories of tasks included within the social domain are conceptually related, they are generally not all bundled together in the same jobs.

Table 2. Bivariate correlations between different task indices

	1. Physical	a. Strength	b. Dexterity	c. Navigation	2. Intellectual	a. Info processing	I. Visual/auditory	II. Codified info	i. Literacy	a. Business	b. Technical	c. Humanities	ii. Numeracy	a. Accounting	b. Analytic	b. Problem solving	I. Evaluation	i. Info search	ii. Abstraction	II. Resolution	i. Creativity	ii. Planning	3. Social	a. Serving	b. Teaching	c. Selling	d. Managing	e. Caring
A. In terms of the content:																												
1. **Physical tasks:** aimed at the physical manipulation and transformation of material things:																												
a. *Strength:* lifting people and heavy loads, exercising strength.	0.89																											
b. *Dexterity:* precisely coordinated movements with hands or fingers.	0.91	0.81																										
c. *Navigation:* moving objects or oneself in unstructured or changing spaces	0.86	0.64	0.62																									
2. **Intellectual tasks:** aimed at the manipulation and transformation of information and the active resolution of problems:	**-0.64**	-0.75	-0.65	-0.48																								
a. *Information processing:*	-0.67	-0.76	-0.67	-0.52	0.95																							
I. Visual and/or auditory processing of uncodified/unstructured information*	0.84	0.63	0.63	0.95	-0.50	-0.55																						
II. Processing of codified information	-0.67	-0.76	-0.67	-0.52	0.95	1.00	-0.55																					
i. Literacy:	-0.66	-0.77	-0.68	-0.51	0.95	0.96	-0.51	0.96																				
a. Business: read or write letters, memos, invoices,...	-0.71	-0.79	-0.73	-0.57	0.91	0.94	-0.56	0.94	0.98																			
b. Technical: read or write manuals, instructions, reports, forms,...	-0.33	-0.51	-0.35	-0.20	0.77	0.75	-0.20	0.75	0.78	0.63																		
c. Humanities: read or write articles or books.	-0.71	-0.79	-0.73	-0.57	0.91	0.94	-0.56	0.94	0.98	1.00	0.63																	
ii. Numeracy:	-0.62	-0.68	-0.60	-0.48	0.87	0.95	-0.55	0.95	0.83	0.81	0.64	0.81																
a. Accounting: calculate prices, fractions, use calculators,...	-0.62	-0.66	-0.60	-0.55	0.78	0.90	-0.59	0.90	0.79	0.82	0.47	0.82	0.94															
b. Analytic: prepare charts, use formulas or advanced maths	-0.52	-0.61	-0.52	-0.34	0.86	0.87	-0.42	0.87	0.76	0.68	0.75	0.68	0.92	0.74														
b. Problem solving:	-0.56	-0.69	-0.57	-0.40	0.96	0.83	-0.41	0.83	0.85	0.81	0.73	0.81	0.72	0.59	0.77													
I. Information gathering and evaluation.	-0.59	-0.71	-0.61	-0.43	0.93	0.82	-0.41	0.82	0.88	0.85	0.74	0.85	0.68	0.57	0.72	0.96												
i. Information search and retrieval	-0.68	-0.74	-0.67	-0.44	0.91	0.83	-0.43	0.83	0.90	0.87	0.72	0.87	0.68	0.58	0.70	0.92	0.98											
ii. Conceptualization, learning and abstraction	-0.50	-0.60	-0.51	-0.37	0.90	0.77	-0.35	0.77	0.82	0.77	0.73	0.77	0.65	0.52	0.71	0.95	0.95	0.88										
II. Creativity and resolution	-0.51	-0.59	-0.49	-0.33	0.89	0.76	-0.36	0.76	0.74	0.70	0.65	0.70	0.71	0.57	0.77	0.94	0.81	0.75	0.85									
i. Creativity	-0.42	-0.51	-0.41	-0.24	0.77	0.62	-0.27	0.62	0.61	0.58	0.54	0.58	0.57	0.44	0.65	0.85	0.69	0.62	0.77	0.95								
ii. Planning/implementation	-0.55	-0.61	-0.52	-0.37	0.92	0.81	-0.40	0.81	0.79	0.75	0.68	0.75	0.76	0.63	0.81	0.95	0.84	0.80	0.85	0.97	0.85							
3. **Social tasks:** whose primary aim is the interaction with other people:	**-0.52**	-0.56	-0.48	-0.40	**0.66**	0.55	-0.37	0.55	0.59	0.63	0.31	0.63	0.46	0.44	0.40	0.71	0.63	0.61	0.64	0.74	0.70	0.73						
a. *Serving/attending:* responding directly to demands from public or customers	-0.35	-0.32	-0.26	-0.35	0.22	0.23	-0.30	0.23	0.24	0.33	-0.06	0.33	0.20	0.34	0.00	0.18	0.11	0.10	0.12	0.24	0.24	0.23	0.69					
b. *Teaching/training/coaching:* impart knowledge or instruct others	-0.41	-0.53	-0.43	-0.21	0.73	0.57	-0.24	0.57	0.56	0.53	0.48	0.53	0.53	0.36	0.65	0.82	0.73	0.70	0.75	0.85	0.81	0.83	0.74	0.13				
c. *Selling/influencing:* induce others to do or buy something, negotiate	-0.61	-0.64	-0.60	-0.51	0.75	0.73	-0.48	0.73	0.74	0.78	0.40	0.78	0.66	0.71	0.51	0.71	0.64	0.62	0.65	0.72	0.65	0.73	0.86	0.65	0.59			
d. *Managing/coordinating:* coordinate or supervise the behaviour of colleagues	-0.46	-0.55	-0.44	-0.31	0.82	0.74	-0.34	0.74	0.72	0.70	0.57	0.70	0.70	0.61	0.70	0.81	0.71	0.69	0.73	0.87	0.78	0.88	0.73	0.22	0.77	0.71		
e. *Caring:* provide for the welfare needs of others.	-0.15	-0.14	-0.14	-0.11	0.16	-0.04	-0.06	-0.04	0.12	0.16	-0.03	0.16	-0.20	-0.22	-0.14	0.32	0.33	0.32	0.32	0.28	0.29	0.25	0.66	0.31	0.43	0.30	0.22	
B. In terms of the methods and tools of work:																												
a. Autonomy	**-0.49**	-0.58	-0.47	-0.41	**0.81**	0.73	-0.40	0.73	0.72	0.72	0.51	0.72	0.67	0.62	0.63	0.81	0.68	0.65	0.71	0.89	0.83	0.88	**0.69**	0.37	0.66	0.75	0.79	0.20
I. Latitude: ability to decide working time, task order, methods and speed.	-0.52	-0.59	-0.52	-0.43	0.83	0.77	-0.45	0.77	0.77	0.77	0.55	0.77	0.71	0.66	0.66	0.81	0.71	0.69	0.73	0.86	0.81	0.84	0.61	0.24	0.61	0.70	0.77	0.15
II. Control (in reverse): direct control by boss or clients, monitoring of work.	-0.49	-0.54	-0.43	-0.37	0.75	0.66	-0.35	0.66	0.65	0.65	0.46	0.65	0.61	0.57	0.58	0.77	0.63	0.57	0.67	0.85	0.78	0.85	0.73	0.43	0.66	0.75	0.78	0.21
b. Teamwork: extent to which the worker has to collaborate and coordinate her actions with other workers	**-0.12**	-0.19	-0.11	-0.12	**0.46**	0.36	-0.12	0.36	0.39	0.34	0.42	0.34	0.30	0.20	0.38	0.52	0.51	0.48	0.56	0.49	0.44	0.49	**0.42**	0.11	0.50	0.34	0.50	0.24
c. Routine	**0.57**	0.54	0.61	0.39	**-0.55**	-0.50	0.39	-0.50	-0.56	-0.60	-0.27	-0.60	-0.40	-0.41	-0.32	-0.55	-0.55	-0.55	-0.51	-0.50	-0.46	-0.50	**-0.60**	-0.38	-0.42	-0.60	-0.42	-0.40
I. Repetitiveness: extent to which the worker has to repeat the same procedures	0.69	0.73	0.74	0.41	-0.79	-0.72	0.44	-0.72	-0.76	-0.76	-0.53	-0.76	-0.61	-0.55	-0.61	-0.80	-0.78	-0.77	-0.73	-0.73	-0.64	-0.75	-0.66	-0.24	-0.66	-0.70	-0.62	-0.36
II. Standardisation: extent to which work procedures and outputs are predefined and encoded in a formalised system	0.08	0.06	0.14	0.02	0.15	0.14	0.02	0.14	0.09	0.01	0.29	0.01	0.19	0.09	0.28	0.15	0.13	0.08	0.20	0.15	0.12	0.17	-0.09	-0.25	0.14	-0.05	0.19	-0.22
III. Uncertainty (in reverse): extent to which the worker needs to respond to unforeseen situations	0.33	0.25	0.29	0.32	-0.43	-0.40	0.31	-0.40	-0.42	-0.42	-0.30	-0.42	-0.35	-0.34	-0.31	-0.43	-0.41	-0.36	-0.45	-0.40	-0.38	-0.40	-0.40	-0.24	-0.28	-0.41	-0.41	-0.18
a. Non-digital machinery (analog)	**0.71**	0.59	0.69	0.59	**-0.42**	-0.38	0.63	-0.38	-0.43	-0.53	-0.04	-0.53	-0.30	-0.35	-0.19	-0.42	-0.42	-0.44	-0.35	-0.38	-0.38	-0.35	**-0.66**	-0.52	-0.39	-0.59	-0.29	-0.53
b. Digitally-enabled machinery (non-autonomous computing devices)	**-0.75**	-0.81	-0.78	-0.58	**0.87**	0.88	-0.58	0.88	0.91	0.90	0.66	0.90	0.77	0.72	0.72	0.79	0.83	0.84	0.76	0.66	0.55	0.70	**0.56**	0.24	0.54	0.68	0.60	0.14
a. Basic ICT (generic office applications)	-0.63	-0.70	-0.69	-0.47	0.85	0.84	-0.50	0.84	0.86	0.85	0.63	0.85	0.75	0.69	0.71	0.78	0.78	0.77	0.74	0.71	0.64	0.73	0.56	0.20	0.59	0.67	0.65	0.15
b. Advanced ICT (programming, admin)	-0.50	-0.58	-0.48	-0.40	0.66	0.63	-0.37	0.63	0.64	0.55	0.72	0.55	0.56	0.39	0.67	0.64	0.66	0.67	0.63	0.57	0.49	0.59	0.26	-0.02	0.43	0.30	0.42	-0.01

Note: *The visual/auditory tasks index is considered as separate index and not included in the aggregate index on information processing (which therefore only refers to processing of codified information) and the overall index on intellectual tasks.

Source: Authors' elaboration on JRC-Eurofound tasks database

Relationship between indices of task content

In terms of task content, and in line with expectations, physical tasks are *negatively* correlated with intellectual tasks (-0.64) and to a lesser extent to social tasks (-0.52). This means that jobs that involve a significant amount of physical tasks tend to involve less intellectual or social tasks, and vice versa. This is particularly the case for physical strength, while it is less so for navigation. The notable exception is visual/auditory processing of uncodified information. This intellectual index is indeed strongly linked to physical tasks (especially navigation, 0.95) because it refers to the physical act of perceiving the environment, and therefore is a crucial component of 'hand-eye coordination'. Furthermore, it is interesting to note there are some distinctions: for instance, technical literacy tasks are not so negatively correlated with physical dexterity or navigation tasks, suggesting that some physically intensive jobs require technical literacy as well. The same applies to creativity and resolution, which have a much weaker negative association with the physical content of tasks, compared to other intellectual task content. This relationship may suggest that performing physical tasks also tends to incorporate some intellectual activities stemming from acquired and tacit knowledge and experience especially in dealing with complex and uncertain production environments (Pfeiffer and Suphan 2015).

On the other hand, social tasks tend to show positive correlations with intellectual tasks (0.66), although again with some important distinctions at a higher level of disaggregation. Overall, managing/coordinating and selling/influencing display more consistently high positive correlations with almost all intellectual tasks (notably in terms of problem-solving), with the partial exceptions of technical literacy and to a lesser extent analytic numeracy. On the contrary, serving/attending and caring show the weakest positive correlations with intellectual tasks indices, at times even negative (there is for instance a clear negative association between numeracy tasks and caring).

The remaining category of social tasks, teaching, is somewhere in the middle: it is positively and strongly associated with problem solving tasks, but much less with information processing.

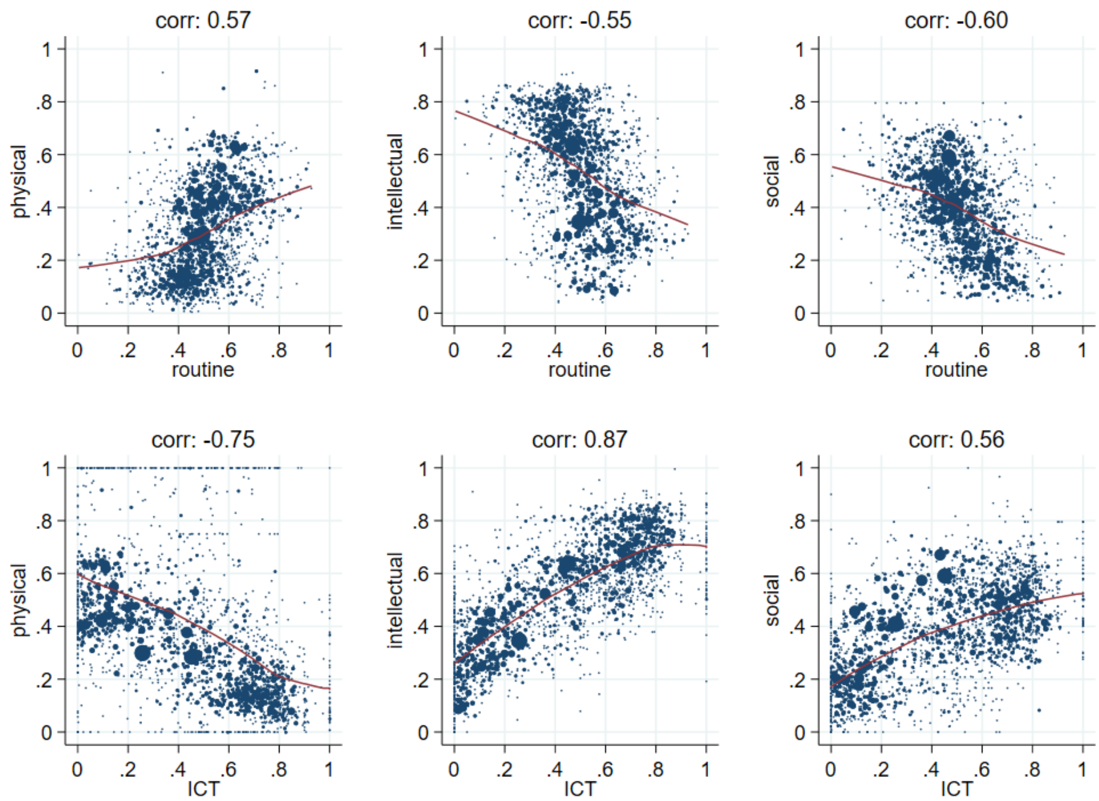
Relationship between the task content, the methods of work and the tools used in the workplace

The correlation between the task content and the task methods and tools domains also reveals some interesting patterns. Physical tasks tend to be associated with less autonomy (both in terms of latitude and control), more routine (particularly in terms of repetitiveness), high use of non-digital machinery and less use of computing devices. The opposite happens with intellectual tasks, again with the notable exception of visual/auditory processing of uncodified information. Figure 3 displays graphically the correlations between the three main dimensions of task content and two key indices of work methods and tools, that is routine tasks and ICT use.

In terms of methods of work, problem solving tasks are those which are more correlated with teamwork (ranging from 0.44 of creativity to 0.56 of abstraction), a dimension which is otherwise less strongly related to other indices of task content. Technical literacy presents milder correlations with all indices of methods and tools, apart from the use of advanced ICT which stands at 0.72. Technical and numeracy (analytic) tasks are those which are less negatively correlated with routine work methods and the use of non-digital machinery, suggesting that there are several industrial-type jobs which require intellectual tasks of such kind.

Social tasks tend to be similar to intellectual tasks when it comes to correlations with methods and tools,

Figure 3. Selected bivariate correlations between task content and routine/ICT tasks



Note: the red line which is graphed on top of the data represents a local linear smooth. Employment-weighted correlations.
Source: Authors' elaboration on JRC-Eurofound tasks database

with the exception of caring and serving, which lie somewhere between physical and intellectual (less autonomy and slightly more repetitiveness, and less computer use compared to other categories of social tasks)[11].

Concluding remarks

In recent years, the taxonomy of tasks proposed by Fernández-Macías *et al*. (2016), and later revised by Fernández-Macías and Bisello (2022), and their accompanying databases of task indices, have been used for various purposes, such as: for the analysis of the distribution and evolution of task content, methods and tools in Europe (Fernández-Macías *et al*. 2016b); to make projections of employment and skills for the future (Cedefop and Eurofound 2018); to build a comparative tasks database based on national sources for 5 EU countries (Fana *et al*. 2020); to identify individual and job factors most likely to be impacted by social distancing measures and practices due to the Covid-19 pandemic (Pouliakas and Branka 2020); to assess which jobs can be done from home and which cannot, and on this basis quantify the fraction of employees that are in teleworkable occupations across EU countries, sectors and socio-economic profiles (Sostero *et al*. 2023); to analyse how job tasks are distributed across social classes, but also the role job tasks play *vis-a-vis* other variables when explaining class belonging and life chances (Gil-Hernández *et al*. 2023); to analyse gender gaps in power and control in the workplace (Fana *et al*. 2023) and the role of tasks in explaining the dynamics of wage inequality (Fana and Giangregorio 2023); to shedg light on how digital technologies affects working conditions (Parteka *et al*. 2022), among other applications.

This article adds three main findings to this body of literature:

1. in the European employment structure, intellectual tasks (in particular, problem-solving tasks) are more prevalent than physical tasks. Social tasks are somewhere in between, with *serving/attending* being the sub-type that is more common. There are relatively high levels of autonomy and teamwork, but also some routine (in particular, with respect to work standardisation). Teamwork and autonomy display a higher dispersion compared to routine indicators, suggesting a more polarised distribution for the first two tasks. In terms of the tools used at work, computing devices and in particular basic ICT are much more frequent than analog machinery, but also than advanced ICT tools.
2. Routine is not unidimensional, Instead, it is a general dimension that is made up of three different types of activities that behave differently across occupations: standardisation, repetitiveness and certainty. The main contrast is between the first two ones: while repetitive activities usually involve high levels of standardisation, the opposite is not necessarily true (as in professional occupations).
3. Physical tasks are negatively correlated with intellectual tasks and to a lesser extent to social tasks. They also tend to be associated with less autonomy, more routine (particularly in terms of repetitiveness), high use of non-digital machinery and less use of computing devices. The opposite happens with intellectual tasks. Social tasks tend to show positive correlations with intellectual tasks.

The wide variety of uses illustrated above shows that the taxonomy and the database have already contributed to a better understanding of work and its relationship with technology and other socio-economic dimensions in European labour markets, and we hope other researchers will continue to find it useful for their own interests and purposes. We hope that the updated and improved version of the database presented in this paper will continue to fuel European research on these topics.

In our view, the main value of this database is that it is built upon a coherent and comprehensive taxonomy of tasks contents, methods and tools (Fernández-Macías and Bisello 2022). Although future users of this data are likely to focus on specific indicators or dimensions depending on their research interests, we would like to encourage them to consider the complementarities and associations between different categories and dimensions of tasks. As we have illustrated, tasks are

11 Some of the correlations between the indices for methods and tools (not shown here) are also interesting. Autonomy is negatively correlated with routine and machinery, but positively with ICT. The relationship between routine and tools is different for the three routine components: repetitiveness is positively correlated with machinery (0.62) and negatively with ICT (-0.75); standardization and uncertainty (in reverse) display a much weaker positive correlation with machinery (0.37 and 0.28) respectively, and relates quite differently to computer use, with correlations close to zero in the former case, and around -0.41 in the latter.

not isolated forms of labour input that just happen to be in productive processes, but building blocks of coherently constructed jobs which are embedded in productive organisations. Any analysis of tasks which focuses on a particular type in isolation risks missing important connections with other types of task content and forms of work organisation.

An important caveat is that the database presented in this paper covers the entire EU15 with a single vector of tasks, without differentiating by country. Thus, possible differences between the task contents, methods and tools across different countries are missing from the database. Previous analysis (Eurofound 2016; Fana *et al*. 2020) has shown that the task contents of occupations (the dimensions of physical, intellectual and social tasks in our taxonomy) are much less country-specific than the dimensions of methods (work organisation) and tools (technology). This is because task contents are more directly linked to the material contents of jobs and to the technical division of labour, whereas work organisation reflects cultural and institutional differences whereas technology use reflects economic development. For these reasons, we encourage future users of this database to complement it with country-specific databases – see, for instance, Fana *et al*. (2020). Although country-specific task databases are less rich in detail, they are still a useful complement to test for possible country variations in the task content of jobs.

A final remark concerns the possibility of a dedicated European survey of task contents, methods and tools. The database presented in this paper (and the companion country-specific database discussed in the previous paragraph) will surely be a useful resource for a better understanding of work in European labour markets, but it still has some limitations that could only be overcome with a new dedicated survey on tasks in Europe. We hope that our contribution raises awareness of the importance of having good and detailed measures of tasks contents, methods and tools, consistently measured at the individual worker level and at different points in time, in order to understand better how technical change and other factors are continuously changing the nature of work and the associated skills demand and job quality. A future European tasks survey could provide that.

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