A Comprehensive Taxonomy of Tasks for Assessing the Impact of New Technologies on Work

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Abstract

In recent years, the increasing concern about the labour market implications of technological change has led economists to look in more detail at the structure of work content and job tasks. Incorporating insights from other traditions of task analysis, in particular from the labour process approach, as well as from recent research on skills, work organisation and occupational change, in this paper we propose a comprehensive and detailed taxonomy of tasks. Going beyond existing broad classifications, our taxonomy aims at connecting the substantive content of work with its organisational context by answering two key questions: what do people do at work and how do they do their work? For illustrative purposes, we show how our approach allows a better understanding of the impact of new technologies on work, by accounting for relevant ongoing transformations such as the diffusion of artificial intelligence and the unfolding of digital labour platforms.

Keywords Tasks · Technological change · Occupations · Labour markets · Structural change · Work organisation

1 Introduction

Until not so long ago, the discussion about the impact of technology on the labour market mostly focused on skills as a mediating factor. Depending on whether a given technology was complementary or substitutive of differently skilled labour (high or low-skilled proxied by educational levels), its impact on labour demand would be positive, negative or neutral. For instance, several influential papers argued that ICT is skills-biased and tended to increase the demand for high skilled labour relative to low-skilled, thus expanding inequalities in the labour market (Violante, 2008).

But the observation of non-linear (polarising) employment trends in some developed economies was difficult to reconcile with this hypothesis of skills biased technical

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change, which led some economists to propose a second dimension (alongside skill level) of bias in the effect of technical change on labour demand: the level of routine of the jobs (Autor et al., 2003). It is important to note that whereas the level of skills is an attribute of workers, the level of routine is an attribute of the jobs themselves. Thus, this concept paved the way for a new approximation to labour market analysis (Autor, 2013). Since technologies are applied in specific production processes, and the labour input in those processes can be classified according to the type of tasks carried out, this approach allows for a much more direct linking of technical change and its employment impact. In fact, the same approach can be generalised to discuss the potential employment impact of any change in the organisation of production: for instance, it has been also used to understand better the impact of trade, by identifying what specific types of task content are easier to offshore in global value chains (Blinder, 2008); or more recently, to estimate how many jobs can be carried out from home, by identifying the types of task content that can be more easily provided remotely (Dingel & Neiman, 2020).

Almost 20 years after the seminal paper that introduced the concept of tasks in contemporary socio-economic research (Autor et al., 2003), we can take stock of the achievements but also of the limitations of this approach. Undoubtedly, the approach has been very fruitful, opening a new sub-field in labour economics and sparking a large literature that covers many different topics in novel and interesting ways. However, there are some shortcomings too.

First, most of the literature takes a piecemeal approach to task analysis, focusing on a few types of task content depending on the objectives of the research. But tasks are combined in specific and coherent ways into actual jobs, and a focus on a few vectors of task content risks missing complementarities or combined effects that can be crucial for understanding the impact of a given technology. Secondly, most of the literature on tasks suffers from some degree of technological reductionism, where labour input is considered as equivalent to machine input given technological feasibility (and relative cost). But work is a social process that requires coordination. Tasks do not exist in isolation, they are coherently bundled into jobs which are performed by people, and the entire process has to be socially organised. This also crucially affects the impact of technologies on employment, or any other change in economic processes that affects labour.

In this paper, we propose a comprehensive taxonomy of tasks for labour market analysis that incorporates the main categories of task content discussed in the recent literature and more, while overcoming the two mentioned limitations. Our framework connects the material content of work (*what people do at work*, with tasks classified according to the type of object and transformation processes) with its organisational form (*how people coordinate their work*, classified according to the main axes of work organisation), as well as the tools used. This taxonomy is mostly intended to be used for assessing the impact of technology on work and employment, and in this paper we also illustrate some possible applications in this respect.

The paper unfolds as follows. Section 2 reviews the recent social sciences literature on tasks and employment. Section 3 discusses what we believe are critical omissions in this literature, which motivates our own more structured and comprehensive approach in Sect. 4. Section 5 presents three illustrative uses of this taxonomy for socioeconomic

research: for describing the distribution of employment in Europe from a tasks perspective, for assessing the potential employment impact of AI, and for comparing work in digital labour platforms with traditional forms of work. Section 6 discusses our contribution to the literature and concludes.

2 A review of Relevant Literature on Tasks

The so called “routinization” (or routine biased technological change, RBTC) hypothesis was first advanced by Autor et al. (2003) who argued that recent technological change, in the form of information and communication technologies diffusion, is biased towards replacing labour in routine tasks. Routine tasks, as opposed to non-routine, are technically easier to codify and automate; these can be either cognitive (such as record keeping or repetitive customer service) or manual (for instance repetitive assembly). Because routine tasks are more frequent in the middle of the skills continuum, while non-routine ones are more likely in the top and bottom ends, this can contribute to polarising trends in the employment structure (see Acemoglu & Autor, 2011 for a discussion).

Several papers defending the RBTC hypothesis and further investigating job polarisation draw on the Autor, Levy and Murnane model (see for instance Goos & Manning, 2007; Autor et al. 2006; Spitz-Oener, 2006; Goos, Manning and Salomons 2010; Autor & Handel, 2013). Autor, Katz and Kearney (2006) and Autor and Handel (2013) consider a three-fold classification of tasks into abstract, routine and manual, where the latter category refers to tasks that require physical effort and dexterity, with low cognitive demand but adaptability and flexibility. Goos et al. (2009, 2010) use instead the concept of service tasks, alongside abstract and routine, denoting those that involve social interaction with clients. Both manual and service tasks tend to be in the non-cognitive and non-routine quadrant.

While the papers cited above build on the same model proposed by Autor et al. (2003), the operationalization of the various categories of tasks is not fully consistent across studies. This is partly due to constraints in data availability, but also lack of clear definitions of rather broad underlying concepts, with the exception of routine tasks. Indeed, in the original formulation of Autor, Levy and Murnane, routine tasks are defined as those that “require methodical repetition of an unwavering procedure” (Autor et al., 2003, p. 1283). More recently, they have been more precisely defined as “sufficiently well understood [tasks] that can be fully specified as a series of instructions to be executed by a machine” (Acemoglu & Autor, 2011, p.1076). However, the level of routine associated with a task depends on how that task is organised rather than on the content of the task itself. As we will discuss later, the routinisation of particular types of work was the historical result of processes of division of labour and reorganisation of production and service provision under particular social conditions: for instance, the routinisation of manufacturing introduced by F. W. Taylor was explicitly aimed at reducing the degree of control over the work process by craft workers (Braverman, 1974). In any case, the model of RBTC would argue that information technologies are substitutive of labour input in routine tasks and therefore tend to reduce labour demand for those tasks.

An important problem of this approach is that it implies that the dimensions of routine and cognitive tasks are distinct, whereas they are in fact strongly linked (in reverse),

both conceptually and empirically. Almost by definition, a task which is routine can be performed with little cognitive effort, and vice versa: non-routine tasks will necessarily involve more active cognitive input. Empirically, there is a strong (negative) correlation between the degree of routine in a task or job, and the degree of cognitive effort involved. In other words, the routine and cognitive dimensions of tasks are strongly associated and correlated (for a discussion, see Fernández-Macías & Hurley, 2017).

The tasks approach has been also used to investigate the impact of offshoring and international fragmentation of production on labour markets. The “new international trade”, which involves a greater international division of labour and different countries adding value to global supply chains, has been described as “trade in tasks”, as opposed to trade in final goods (Grossman and Rossi-Hansberg, 2006, 2008). The literature identifies some types of tasks which are easier to trade than others, namely those which require codifiable rather than tacit information (Leamer & Storper, 2001), can be summarised in deductive rules, and are therefore more routine (Levy & Murnane, 2004), and those which do not require face-to-face personal communication and/or contact with end users (Blinder, 2009). Besides routine, social interaction is therefore emphasized in these studies as a key aspect of jobs to understand their offshorability.

3 Some critical Omissions of the Task-Based Approach

According to the main proponent of the tasks approach in labour economics, tasks can be simply defined as discrete units of work activity that produce actual output (Autor, 2013). Depending on the complexity of a given production or service provision process, it may require the combination of different types of tasks, in the same way as it may require different types of raw materials. Therefore, this approach has a strictly technical view of the economy, seen as a mechanical process of transforming inputs into outputs.

One of the main aims of the approach is to understand better the potential substitution of human workers by machines for the performance of some types of tasks. Work is therefore understood as any kind of active input into the economic process, which can be performed by human beings or machines (or animals, we could perhaps add). Given technical feasibility, which factor will perform a task in a particular process will depend on the principle of comparative advantage: “comparative advantage in production means that the factor with the lowest economic cost of performing a task is assigned to that task. Economic cost in turn reflects both a factor’s technological capability and its opportunity cost” (Autor, 2013, p. 5). In other words, depending on what is technologically feasible, a task will be performed by the cheapest factor.

Nevertheless, in this approach human labour has still a certain primacy over machine input in the production and service provision process. Because it is intrinsically flexible and adaptable, human labour has historically preceded machine input in the performance of most types of tasks (Autor, 2013, p. 4). The typical historical sequence of automation would be one in which human workers first improve and codify the performance of a particular task, which can then be taken up by machines once technology allows for it. This does not necessarily mean that all tasks will end up being carried out by machines: again,

that will depend on the comparative advantage of physical capital over labour in each particular case.

To our understanding, this approach provides the basis for an improved knowledge of the nature of labour demand. It has clear microeconomic foundations and it seems particularly useful for understanding the process of automation of some types of jobs, and more general structural developments of labour demand. However, because it largely ignores the ways in which work processes are socially embedded, it has important limitations.

First, the idea that humans and machines can be perfect substitutes (depending on technology and relative costs) for the performance of some types of work or tasks can be misleading. In a narrow sense, we agree that machines can perform certain types of tasks. However, a crucial difference is that machines have no real *agency* (capacity to act independently, or free will) as while human workers do (at least, until a general artificial intelligence comes into existence), and therefore there must always be human labour behind (for designing, controlling or maintaining the machines, and to deal with unforeseen situations). This is why even the most advanced industrial robots can be understood as very sophisticated tools (their main effect being the continuing increase of the productivity of the few remaining industrial workers; Aghton et al., 2017).

Second, the fact that human beings have real agency implies that their input into the economic process requires their active cooperation. The organisation of production will not only have to maximise the technical efficiency of labour inputs but use forms of work organisation that ensure the cooperation of employees. Historically, this cooperation has been achieved by very different means, from the implicit coercion of workers' in-miseration in early industrial capitalism to the active consent and trust searched by contemporary human resource practices (Heisig & Littek, 1995). But this fact also affects very significantly the organisation of production itself. For instance, the extreme division of labour and standardisation of processes of Taylorism/Fordism were explicitly aimed at increasing the degree of managerial control in factories (Braverman, 1974). Furthermore, ensuring the active cooperation of workers in production is a task (or set of tasks) in itself, and requires a significant amount of labour input for supervisory, managerial and control activities. Those tasks are not necessary in a technical sense, and therefore cannot be explained from a purely technical perspective: they are necessary in a *social* sense, to ensure the cooperation of workers (Green, 2013).

Third, work tasks rarely exist in isolation. In the vast majority of cases they are coherently bundled into *jobs*.¹ We may think about tasks as units of work from the perspective of production (or service provision), but jobs are the units of labour demand from the perspective of firms and workers. In fact, jobs are not only bundles of tasks but also positions within the social structure of productive organisations, giving differential access to social status, resources and life chances (Cohen, 2013, 2016; Grant et al., 2011; Parker et al., 2017). All these aspects also affect the distribution and organisation of tasks in ways that are at least partly independent from technical considerations. For instance, the allocation of tasks to jobs (the *job description*) is often the object of struggle between managers and workers, even collectively bargained (Cohen, 2016).

¹ Whereas this is true in general in the regular economy, it may be changing as a result of the application of digital technologies to work organisation. Digital labour platforms, for instance, do in many cases coordinate labour transactions in which the unit of work is the task and not the job. Currently, this new form of work is extremely marginal, accounting for at most 1 or 2% of the labour market (Pesole et al., 2018), but it may become more prevalent in the future. In Sect. 4, we discuss this issue with more detail.

Fourth and last, tasks are also socially embedded because the structures of production and service provision of any economy necessarily reflect the structures of consumption of society. The change in the contents and types of tasks in production will ultimately reflect how societies change in their tastes and preferences, in their institutions and organisational forms. This is why there can be, even within similarly developed capitalist economies, significant differences in the prevalence of different types of tasks in their productive structures (and the associated occupational categories). Social-Democratic models, for instance, have tended to expand the public provision of social services and to reduce the weight of low-paid manual service occupations, while Market-Oriented models often moved in the opposite direction (Esping-Andersen, 1999). This, which can be associated to different patterns of structural change in employment (job polarisation in the latter, structural upgrading in the former), can be also reflected in a smaller weight of non-routine manual tasks in Social-Democratic countries relative to Market-Oriented economies (Oesch, 2015). This would be again a development driven at least partly by social rather than technical developments, and therefore cannot be fully understood with a strictly technical framework.

Hence a crucial building block for our proposed approach is that the structure and types of tasks in an economy do not only reflect the technical nature of the production and service provision process and the structure of demand, but also its social organisation according to the four previous points. The next section presents in detail our proposal for a comprehensive taxonomy of tasks, based on the reviewed literature and identified shortcomings.

4 A proposal for a Comprehensive Taxonomy of Tasks

As discussed in Sect. 2, until now the related economic literature primarily focused on simplified classifications of tasks based on rather broad underlying concepts, such as cognitive/abstract tasks (as opposed to manual), routine tasks, and in some cases social/interactive/service tasks. Our approach puts together these main types of tasks, while at the same time substantially increasing the level of detail in the classification and adding new dimensions to fill in what we consider to be important gaps. Additionally, our approach incorporates elements of work organization into the classification of tasks, acknowledging the interdependencies between technological and organizational change (see for instance Bresnahan et al., 2002; Greenan, 2003; Gale et al., 2002). In doing so, our taxonomy proposes a link between skill and task-based approaches to measure what people do at work with a more organisational view on how they do it. The proposed classification connects the material content of work (i.e. extent to which workers engage different types of tasks) with the organisational form of work (i.e. methods and tools used to do things).

Table 1 below presents our proposal for a taxonomy of tasks within jobs.² As a first step, tasks can be classified in two axes that are conceptually different: one which refers to the content of work activity (A in Table 1) and the other which refers to the methods and tools used at work (B in Table 1). In very simple terms, we can think about those two axes as the *what* and the *how* of work activity. In what follows we present and discuss in detail each component of the taxonomy.

² A previous version of the taxonomy was presented in Fernández-Macías et al. (2016).

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:
<p>1. Physical tasks: aimed at the physical manipulation and transformation of material things:</p> <ol style="list-style-type: none"> <i>Strength:</i> lifting people and heavy loads, exercising strength. <i>Dexterity:</i> precisely coordinated movements with hands or fingers. <i>Navigation:</i> moving objects or oneself in unstructured or changing spaces <p>2. Intellectual tasks: aimed at the manipulation and transformation of information and the active resolution of problems:</p> <ol style="list-style-type: none"> <i>Information processing:</i> <ol style="list-style-type: none"> Visual and/or auditory processing of uncoded/unstructured information Processing of codified information <ol style="list-style-type: none"> <i>Literacy:</i> <ol style="list-style-type: none"> Business: read or write letters, memos, invoices,... Technical: read or write manuals, instructions, reports, forms,... Humanities: read or write articles or books. <i>Numeracy:</i> <ol style="list-style-type: none"> Accounting: calculate prices, fractions, use calculators,... Analytic: prepare charts, use formulas or advanced maths <i>Problem solving:</i> <ol style="list-style-type: none"> Information gathering and evaluation. <ol style="list-style-type: none"> Information search and retrieval Conceptualization, learning and abstraction Creativity and resolution <ol style="list-style-type: none"> Creativity Planning <p>3. Social tasks: whose primary aim is the interaction with other people:</p> <ol style="list-style-type: none"> <i>Serving/attending:</i> responding directly to demands from public or customers <i>Teaching/training/coaching:</i> impart knowledge or instruct others <i>Selling/influencing:</i> induce others to do or buy something, negotiate <i>Managing/coordinating:</i> coordinate or supervise the behaviour of colleagues <i>Caring:</i> provide for the welfare needs of others. 	<p>1. Methods: forms of work organisation used in performing the tasks:</p> <ol style="list-style-type: none"> <i>Autonomy</i> <ol style="list-style-type: none"> <i>Latitude:</i> ability to decide working time, task order, methods and speed. <i>Control (in reverse):</i> direct control by boss or clients, monitoring of work. <i>Teamwork:</i> extent to which the worker has to collaborate and coordinate her actions with other workers <i>Routine</i> <ol style="list-style-type: none"> <i>Repetitiveness:</i> extent to which the worker has to repeat the same procedures <i>Standardisation:</i> extent to which work procedures and outputs are predefined and encoded in a formalised system <i>Uncertainty (in reverse):</i> extent to which the worker needs to respond to unforeseen situations <p>2. Tools: type of technology used at work:</p> <ol style="list-style-type: none"> <i>Non-digital machinery (analog)</i> <i>Digitally-enabled machinery</i> <ol style="list-style-type: none"> Autonomous (robots) Non-autonomous <ol style="list-style-type: none"> Computing devices <ol style="list-style-type: none"> Basic ICT (generic office applications) Advanced ICT (programming, admin) Specialised ICT Others

4.1 The Content of Tasks

The taxonomy of task contents takes into account the object of work as transformative activity, the type of transformation involved, and the skills typically required. Since the skills requirement of tasks tend to be associated with different automation suitability levels, this classification can be used to assess the potential impact of existing or forthcoming technologies on the labour market, as we will discuss later. This is also the approach of some recent papers such as Arntz et al. (2017) and Nedelkoska and Quintini (2018).

At the highest level of generality, this taxonomy differentiates tasks according to the object upon which the task is performed: physical tasks (that operate on things), intellectual tasks (that operate on ideas) and social tasks (that operate on people). This classification is conceptually consistent with a previous taxonomy of work activities developed by psychologist Sidney Fine in 1955 who suggested that all work is at least to some extent oriented towards things, data or people (although with variations in task complexity).³ Within each of the three high-level categories that we identified (i.e. physical, intellectual and social), different sub-categories of tasks are differentiated on the basis of the type of transformation involved and the typical skills requirements.

Physical tasks would encompass the types of activities that the literature sometimes refers to as “manual”. We split it into three sub-categories:

³ Magnusson and Tåhlin (2018) note the close correspondence (and empirical correlation) between Fine’s trichotomy of work and the three main kind of job tasks identified by Goos and Manning (2007), and in turn inspired by in the seminal work of Autor et al. (2003), that is: service, abstract and routine.

- The first one, *strength*, refers to the pure exertion of muscular power (for instance, lifting people and heavy loads), and it is probably the category of labour input that has been most significantly reduced by technological change since the dawn of civilisation (even before machines, the domestication of animals enabled a very significant reduction of human input for this type of task). Still, it remains a significant component of some types of jobs nowadays, so we include it in our classification.
- The second one is *dexterity*, which involves precise movements with hands or fingers and corresponds most directly with the concept of manual tasks. As in the previous case, technological change (in particular, *mechanisation*) has reduced significantly the amount of labour input in this kind of task: but it still represents a significant share of labour, even if it is in secular decline.
- The third one is *navigation*, which consists of moving objects or oneself in unstructured or changing spaces, through appropriate routes and in the presence of other objects or agents. This type of task content is surprisingly difficult to automate, because it requires the combination of several highly complex but low-level cognitive functions which we do not even understand entirely (Wolbers & Hegarty, 2010); however, digital sensors and AI techniques are making significant inroads in the automation of this type of task in recent years.

Intellectual tasks refer to information processing and problem solving, and are similar to the concept of cognitive tasks found in the literature (Kautz et al., 2014). Until relatively recently, intellectual tasks tended to expand as technological change reduced the amount of human labour necessary to carry out physical tasks: but particularly in the case of information processing tasks, advances in computing have allowed for a large-scale substitution of intellectual human input by machines in recent decades. Each of the two categories of intellectual tasks is further sub-divided as follows:

- *Information processing* tasks are split into:
 - Visual and/or auditory processing of uncoded/unstructured information, which as the previous category of “navigation” relies on complex low-level cognitive functions not completely understood, and are also difficult to automate (although this may be rapidly changing with the latest techniques in AI and machine learning; see Craglia et al. 2018).
 - Processing of coded information, either text (literacy: business, technical and humanities) or numbers (numeracy: accounting and analytical). Computers are mostly used for automating or complementing human labour for this type of task content, which is still very prevalent as we will see later.
- *Problem solving* tasks are further divided into:
 - The gathering and evaluation of information, which comprise both information search and retrieval (which currently often imply the use of computers), but also conceptualisation, learning and abstraction;
 - The creativity required for finding a solution and its planning/implementation.

Finally, *social tasks* are those aimed at the interaction with other people. As for intellectual tasks, the amount of labour performing this type of tasks content has grown as technological progress reduced the amount of physical labour input needed. But unlike information processing, even the most advanced machines are still incapable of replacing humans for social interaction, so labour demand is likely to continue growing in this category in the foreseeable future.

Compared to the other dimensions of our taxonomy, there is less literature differentiating types of social interaction tasks (in most cases, there is only a generic “social interaction” task dimension). However, we believe it is also important to differentiate types of social interaction, so we propose five sub-categories on the basis of a detailed inspection of sectors and occupations in services:

- *Serving/attending* responding directly to demands from public or customers.
- *Teaching/training/coaching* imparting knowledge or instructing others.
- *Selling/influencing* inducing others to do or buy something, negotiating.
- *Managing/coordinating* coordinating or supervising the behaviour of others.
- *Caring* providing for the welfare needs of others.

Although the social dimension is obviously linked to the service sector of the economy, it is important to note that they are by no means synonymous: our focus is on the content of work as a transformative process, and some types of services are actually aimed at the transformation of the physical environment (for instance, cleaning services) or the processing of information (such as business or legal services), and thus do not necessarily correspond to the social dimension of our taxonomy.

4.2 The Methods and Tools of Work

The methods and tools of work, on the other hand, refer to: (1) the ways work is organised and; (2) the physical objects used for aiding the production or service provision process. In this sense, they are less dependent on what is being produced and more on the technology and social organisation of production. Therefore, they are more historically and institutionally contingent. For the production of the same goods or services, different societies or organisations can use significantly different methods and tools at different points in time.

The category of *methods* (work organisation) is broken it down into three categories following the main dimensions identified in the specialised literature:

- *Autonomy*, which refers to the degree of latitude of workers for carrying out their tasks, and the monitoring and control exercised over them (the latter measured in reverse).
- *Teamwork*, which refers to the direct collaboration with small groups of co-workers.
- *Routine*, referring to the degree of repetitiveness and standardisation of the work processes, but also the need to respond to unforeseen situations (in reverse).

The inclusion of routine in this domain of our taxonomy may seem surprising, since many previous papers consider it a type of task content (rather than a method), with a similar status as cognitive/intellectual tasks. In our view, the degree of routine involved in a task is not an aspect of task content as such, but an aspect of how tasks are organised in a particular work process. The same type of task content (in terms of the object of the

transformative process of work, as classified in the first axis of our taxonomy) can be carried out with a low or a high degree of routine: in this respect, the routinisation of a task should be understood in itself as part of the process of organisational change, rather than as something given by the material nature of the production process.

Finally, we also included two components measuring the use of “tools” (technology) at work:

- *Non-digital machinery*, that is, use of analog mechanical devices.
- *Digitally-enabled machinery* use of either autonomous digitally enabled machines (i.e. advanced robots), computing devices (differentiating by the level of skills they may require) or other digitally-enabled machinery.

5 Using the Taxonomy for Socio-Economic Research: Three Illustrations

In this section, we will present three illustrations of possible uses of our proposal for socio-economic research, with a focus on the implications of recent technological change on work and employment. The first illustration is about the use of our taxonomy to describe the distribution of employment in an economy across different types of task input; the second, about the use of our taxonomy to assess the implications of recent AI developments for the labour market; and the third, about the use of our taxonomy for bridging the regular labour market and the labour market of digital labour platforms. In the three cases, the examples used refer to real research which is currently in progress.

5.1 Describing the Distribution of Employment from a Task Perspective

The proposed taxonomy can be used to describe the distribution of employment across different types of task input with a high degree of granularity, in a way which is independent from the traditional classifications of employment in terms of occupation and sector but complementary to them. In fact, the proposed taxonomy of tasks can be used to empirically assess whether the classifications of occupation and sector really capture distinct and internally consistent bundles of tasks, as implicitly assumed.

For illustration, Fig. 1 shows the distribution of task contents, methods and tools following the structure of our taxonomy in the four biggest employing jobs in the EU on the basis of real data from the 2015 European Working Conditions Survey (EWCS), the OECD’s Program for the International Assessment of Adult Competencies (PIAAC) Survey, and a European (Italian) version of the O*NET database of occupational contents (Indagine Campionaria delle Professioni, ICP 2012). For each of the task categories, data at the job level (2-digit occupation by 2-digit sector combinations) was compiled using the above mentioned surveys and occupational databases, weighted with employment data from the European Labour Force Survey, and standardised to a 0/1 scale that reflects the intensity to which a given job implies doing a given type of task content. A detailed description of the sources and methodology used for the construction of task indices can be found in Bisello et al. (2021). Because of their importance in terms of employment, the comparison of tasks profiles among these jobs is very illustrative, although not representative of the overall employment structure.

Fig. 1 Task profile of the four biggest jobs, EU15. *Note:* Employment shares in each job, derived from the European Labour Force Survey data in 2019, were used for weighting the indices. The radar chart to the left shows the scores for the task indices on the content of work, while the chart to the right refers to methods of work and tools. The United Kingdom was not included in the EU-15 aggregate. The full tasks database can be downloaded from https://ec.europa.eu/jrc/sites/jrcsh/files/jrc124124_database.zip

In terms of job content, the distribution of social and intellectual tasks varies more than physical tasks across the four jobs. In terms of the latter, more heterogeneity is found for dexterity, with the lowest score for teaching professionals and highest for personal service workers and health professionals. As for intellectual tasks, the biggest divide between jobs is found in terms of problem solving tasks: teaching and health professionals are characterised by very high scores (around 0.8) of gathering and evaluation of information, as well as creativity, while sales workers and personal services workers record much lower values (between 0.3 and 0.5). The above findings suggest that physical and intellectual tasks are not always inversely correlated as health professionals, for instance, show high values for both physical and intellectual task content simultaneously.

Figure 1 also reveals that social tasks clearly differentiate categories of workers, with each job being characterised by a very high intensity (above 0.8) in at least one specific type of social tasks (health professional score very close to 1 in caring tasks, sales workers in serving/attending tasks). Data also indicate that high-skilled workers tend to have a more multifaced profile in terms of social tasks, as they carry out different social activities with medium or high intensity, while low-skilled workers have high scores only in terms of serving/attending and rather low for other social tasks. Finally, the smallest differences across the four displayed jobs are found in terms of selling/influencing and managing/coordinating tasks.

In terms of methods of work and tools, average scores are more similar across jobs, with the exceptions of control and repetitiveness (for which an inverse relationship clearly emerges for high-skilled jobs) and the use of ICT, which is quite heterogenous across the shown jobs (high-skilled professionals are characterized by substantially higher scores compared to sales and personal care workers). Previous analysis shows that methods and tools of work are less occupation-specific and tend to vary more across countries and sectors instead, as they reflect institutional and cultural differences, as well as economic development levels (Fana et al., 2020). Furthermore, the analysis highlights the importance of measuring routine as a multi-dimensional concept and it challenges the idea that workers

Fig. 2 Average task scores for EU15. *Note:* Employment shares in each job, derived from the European Labour Force Survey data in 2019, were used for weighting the indices. The full tasks database can be downloaded from https://ec.europa.eu/jrc/sites/jrcsh/files/jrc124124_database.zip

performing complex intellectual tasks, such as problem solving, have lower levels of standardisation and more often need to respond to unforeseen situations.

If we calculate the average task scores for all workers in all sectors and occupations in the EU15, we get an approximation to the task profile of the average worker in Europe, as shown in Fig. 2. According to this approximation, the most frequent type of task content in European employment is intellectual, in particular problem-solving tasks, whereas physical task content has a much lower prevalence and social tasks are somewhere in between. In terms of task methods and tools, there are relatively high levels of autonomy but also some routine (in particular with respect to work standardisation), and ICT tools⁴ are much

⁴ Due to lack of suitable sources, task scores for robotic technology and specialised ICT tools are not available.

more frequently used than machinery. Figure 2 also shows the dispersion of values around the mean, which 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 common task types; whereas business and humanities literacy and information search and retrieval have high scores but high dispersion, suggesting a more polarised distribution (some jobs have a lot of task content of those types, other jobs very little).

To wrap up this section, we will finish with an exploratory analysis of the correlation between the average task scores across occupations (defined at the ISCO-08 two-digit level) and their wage levels. For this, we use external data on wages obtained from the European Structure of Earnings Survey (SES) from 2014. The hourly wages of respondents have been rescaled to an index relative to the average national wage, then averaged by occupation, and then averaged across 10 European economies (those from EU15 available in ESES). Thus, the wage scores represented in the vertical axes of Fig. 3 reflect the average wage level of occupations, whereas the horizontal axes represent 20 selected task indicators from our taxonomy. Each occupation is represented by a bubble, its size representing its share of total employment in EU15.

Although several of the task indices shown have a clear and relatively strong correlation with average occupational wages, the direction and intensity of this correlation vary significantly. The three indices of physical task content and the index of uncoded information processing (tasks involving visual or auditory perception) have a *negative* correlation with wage levels: especially, occupations with high scores in physical strength and dexterity tend to have lower than average wages. On the contrary, intellectual task contents (processing of codified information, evaluation of information and problem resolution) show strong positive correlations with occupational wages. As for social task contents, managing is very strongly correlated with higher wages, while teaching and selling show moderate positive correlations and serving and caring no correlation at all.

With respect to the indicators of task methods, the two indicators of autonomy (latitude and control in reverse) are strongly and positively correlated with occupational wages, whereas teamwork is only mildly so. Interestingly, two of the indicators of routine (repetitiveness and certainty) are moderately but negatively correlated to occupational wages, whereas standardisation displays no correlation at all. And while use of ICT tools are strongly and positively correlated with occupational wages, the use of machinery shows no relevant correlation.

In short, this simple exploratory analysis shows that our task indicators have in many cases a relevant predictive capacity for occupational wages, which is an obviously important attribute of jobs which is not directly linked to our tasks measures and thus can be understood as a form of external validation. The fact that the correlation between our task indicators and occupational wages varies in strength and direction in meaningful ways also shows that they measure qualitatively different attributes of work.

5.2 Using the Taxonomy to Assess the Employment Impact of AI: Some Preliminary Considerations

At present, no automation technology has the sufficient level of generality to perform all of the task content associated with any existing occupation, and thus trying to assess the potential impact on employment of technological change at the level of full occupations

Fig. 3 Correlations between task indicators (EU15) and wage occupational indices (EU10). *Note:* Employment shares in each job, derived from the European Labour Force Survey data in 2019, were used for weighting the indices. The wage indices were obtained from the European Structure of Earnings Survey (SES) from 2014. The full tasks database can be downloaded from https://ec.europa.eu/jrc/sites/jrcsh/files/jrc124124_database.zip

is bound to fail. The effect of automation technologies on work is better understood at the level of specific tasks (Tolan et al., 2020).

In this respect, the high level of granularity in the classification of task contents of our proposed taxonomy can be used to identify on what types of work a given technology is

likely to impact. For instance, the steam engine is primarily a technology for generating and transmitting power to mechanical processes: thus, its primary effect was on physical strength task content, and as the mechanical transmission and manipulation technology gained precision, it could also replace (or transform) manual dexterity task content. Computers are another good example: they are essentially information processing machines, and thus their main impact has been in terms of numeracy and literacy information processing task content: again, either replacing labour input for the performance of those types of task (as in calculating tasks, now rarely performed by hand) or complementing it (as in many text processing tasks).

For our purposes, we can define artificial intelligence as a set of techniques that allow machines to mimic human cognitive functions for the performance of some specific types of tasks (Craglia et al., 2018). AI research has made significant progress in recent years in the automation of some specific tasks which until recently were privative of humans, such as some types of problem-solving (especially when the parameters of the problem are explicit and well delimited, as in board games) or visual pattern recognition. But the ability to perform *any* task currently performed by humans would require machines that can perfectly mimic the full range of human cognitive abilities (strong AI), which is very far from current possibilities. So again, the potential impact of recent AI developments on human labour is better understood at the level of specific tasks, rather than full occupations.

In a recent paper, Tolan et al. (2020) use our proposed taxonomy to assess the potential impact of recent advances in AI on employment. The basic idea behind this approach is that each type of task in our taxonomy (identified at the most detailed level) requires one or more human cognitive abilities,⁵ and the same list of human cognitive abilities can be also used to classify recent progress in the different domains of AI research.⁶ In other words, human cognitive abilities can be used as an intermediate layer to map recent progress in AI research to the specific labour tasks that they can impact. For instance, manual dexterity tasks require the human abilities of sensorimotor interaction and attention and search; the intensity of AI research on sensorimotor interaction is relatively small according to the assessment made in the paper, while attention and search has an intermediate level of intensity of AI research. Therefore, this approach would suggest a small potential impact of current AI research on manual dexterity tasks. Since we know which occupations (and how many people) involve manual dexterity tasks in Europe (as discussed in the previous section), this assessment can be generalised to the whole of European employment.

However, such an exercise can only assess the technological feasibility of replacing or complementing human labour for the performance of specific tasks. To move beyond an assessment of technological feasibility, two additional aspects need to be considered: first, the relative cost of labour vs. automation for the performance of the task in consideration (Autor, 2013); and second, the forms of work organisation which are associated with such a task or tasks. For both purposes, our approach can provide a useful starting point. For assessing the relative cost of labour in specific tasks, having a detailed measurement of task contents for occupations/sectors with known wage levels can be the basis of a good approximation. And secondly, for taking into account the mediating role that work

⁵ Both abilities and skills are relevant to task performance, but from a human perspective abilities are innate (and lower level) while skills are acquired through a combination of abilities, experience and knowledge (Tolan et al., 2020).

⁶ In Tolan et al. (2020), progress in AI research is proxied by the amount of research output across 328 AI Benchmarks (standardized contests linked to specific problems to be solved using AI algorithms).

organisation plays for the automation of specific tasks, the fact that our proposed taxonomy keeps work organisation as a separate dimension to task content can be very useful.⁷

Since this second point is rarely discussed in the literature, it is worth discussing it with some more detail. Production processes (as economic activity in general) entail a significant amount of uncertainty. Humans are naturally good at dealing with this uncertainty, because they can generalise from previous experience and knowledge, adapt goals and planning, and negotiate cooperative solutions. Machines (even those equipped with the most advanced AI techniques) lack those attributes and are therefore very limited in dealing with uncertainty: they can replace labour only to the extent that this uncertainty has been removed from a given economic process. The three indicators of work organisation of our taxonomy (autonomy, teamwork and routine) can be understood as proxies of the extent to which uncertainty has been removed from a particular work process: if workers have low levels of autonomy at work, do not have to cooperate much with other workers, their tasks are highly repetitive and standardised and do not require dealing with unforeseen problems, we know that the work they do is susceptible to automation (to the extent that the tasks they do can be replaced by existing technology). If their work involves high levels of autonomy and cooperation, has low levels of repetitiveness and standardisation and does require dealing with unforeseen problems, their labour input will be very difficult to replace by machines even if those machines can technically perform many of the tasks they do at work (and in this case, the impact of AI is more likely to be complementarity rather than substitution). Thus, the work organisation dimension of our taxonomy can be used to complement and make a more realistic assessment of technological feasibility of automation of different types of tasks content, as previously discussed.

5.3 Using the Taxonomy to Compare Digital Labour Platforms with Traditional Work

Because most labour input is provided by human beings within the context of socially coordinated economic processes, the real unit of labour input in the labour market and productive organisations is the job rather than the task. As previously argued, jobs are coherent bundles of tasks to be carried out by specialised workers, which correspond to positions within productive organisations. If what was exchanged in labour markets was the individual labour input into specific tasks, coordinating any minimally complex process would be exceedingly difficult. That is why in practice the unit of labour input in the economy is the job rather than the task, even if from a technical (engineering) perspective the task can be the minimal unit of labour input as discussed in this paper.

But this may change with the increasing use of digital platforms for the coordination of economic activity (Pesole et al., 2018). Platforms can be defined as digital networks that coordinate transactions in an algorithmic way. They are the native form of economic coordination in the digital economy, and they represent something genuinely distinct from markets and organisations (platforms have elements of both, because they are both spaces for exchange and a set of rules and mechanisms for coordinating that exchange). But most importantly for our purposes, their use of big data and algorithmic management allow them to coordinate extremely complex processes with very large numbers of participants

⁷ A third and also potentially crucial factor determining the automation of specific tasks would encompass societal/cultural aspects, ranging from social desirability to regulation.

in a very efficient way. Their use for coordinating work-related services (digital labour platforms) allows the direct exchange of task-level labour services. In other words, in the still marginal but growing segment of digital labour platforms, the unit of labour input is indeed the task rather than the job.

This makes the analysis of employment in digital labour platforms very difficult compared to the traditional labour market (Pesole et al., 2018). Whereas in regular labour markets, most people have jobs of a certain entity and regularity (with a set of attributes and conditions that can be easily measured), in digital labour platforms people can provide a myriad of different tasks through different platforms, potentially with different attributes and conditions. How to compare the two types of work? Our taxonomy can be used to link the regular labour market and digital labour platforms. As illustrated in a previous section, using our taxonomy we can describe the regular labour market from a task perspective with a high degree of granularity and detail. But our taxonomy can also be directly applied to classify the tasks provided through digital labour platforms (contrary to the traditional classification of occupations, which does not apply to digital labour platforms because it presupposes a bundling of tasks into organisational positions that does not exist in them).

Thus, our taxonomy could be used to bridge the measures of labour input in regular labour markets and in digital labour platforms. The labour input provided through digital labour markets can be classified within the task content part of our taxonomy: in most cases, the task will clearly and only relate to a single specific category in our taxonomy; in some cases, it may involve more. For instance, much of the labour input provided via Amazon Mechanical Turk (which, incidentally, uses internally the term “Human Intelligence Tasks” or HITs to classify the different types of services bought and sold; see Williams et al., 2019) would fit into one of the categories of the “intellectual” tasks of our index, either “visual processing of uncoded information” (as in the tagging of pictures), or “literacy—business” (as in the writing of small ads or notices), or “information search and retrieval” (as in website feedback). Personal service tasks such as Deliveroo rides would mostly involve physical tasks as “navigation” or “strength”, whereas Uber drives are essentially tasks involving “navigation” with some “serving/attending” social interaction. The dimensions of methods and tools of our taxonomy could be also used for a multidimensional classification of labour input in digital labour platform. Whereas Amazon Mechanical Turk tasks are typically highly routine (repetitive and standardised, with low autonomy), high-skilled professional platforms often involve non-routine high-autonomy work organisation, in some cases even carried out in teams.

6 Discussion and Conclusions

In recent years, the increasing concern about the labour market implications of technological change has led economists to look more in detail at the structure of work content and job tasks. Tasks are what people do at work, and the introduction of a new technology at work will generally change (remove, transform or add) specific types of task content. Since different types of task content require different skills and specialisation, when technology changes the distribution of tasks it also indirectly changes the demand for different types of labour, and thus the structure of inequality in the society at large.

Although the tasks approach only recently gained popularity in economics, after the publication of the seminal work by Autor et al. (2003), there is a very long tradition of research on tasks in the Social Sciences. This tradition goes back to classical Political

Economists such as Adam Smith (who discussed explicitly the effect of the division of labour on tasks and skills in chapter 5, book 1 of the *Wealth of Nations*) or Karl Marx (who considered the task-biased effect of industrial technology to be deskilling in many of his classical works, for instance in *Wage Labour and Capital*). But the concept of tasks (and in general, any discussion of the production process as such) effectively disappears from economics with the marginal revolution. Neoclassical economics tended to ignore what happens within productive organisations, conceived as black boxes that take skills, capital and raw materials as input and produce goods or services as outputs (Debreu, 1959, pp. 37–38). The analysis of tasks within production and how technology and other factors change them was until recently a subject for sociologists of work (in particular those following Braverman and the labour process tradition), social psychologists (for instance, in work organisation research) and occupational epidemiologists (who conducted research on working conditions and health and safety at work).

However, the recent emphasis of economics on tasks has tended to focus on a narrow set of task dimensions. In particular, it has tended to focus on the level of routine of work tasks as the most relevant attribute for determining the impact of technology on work and labour demand, although other aspects such as the cognitive or manual content of tasks, or social interaction have also been discussed. In this paper, we have reviewed this recent socio-economic literature on tasks and occupational change, trying to identify the main attributes of tasks with socio-economic relevance but also trying to identify critical omissions in this literature. Incorporating insights from other traditions of task analysis in the Social Sciences (in particular, from the labour process approach derived from the seminal work by Braverman in the 1970s, but also from recent research on skills, work organisation and occupational change; see for instance Green, 2013; Cohen, 2016; Fernández-Macías & Hurley, 2017), in this paper we proposed a comprehensive taxonomy of tasks. This taxonomy differentiates on the one hand task content in terms of the object of work as transformative activity (with physical, intellectual and social tasks being defined by their respective objects: things, ideas and social relations), and on the other hand, the methods of work organisation and the tools used for work. Our proposal tries to be not only comprehensive but also very granular, with a nested structure that allows to focus on a given level of detail depending on research objectives. It incorporates all the task dimensions identified in the contemporary literature reviewed, but also several dimensions not generally taken into account but which either derive from other Social Sciences traditions or are implied by the structure of our taxonomy. Another added value of our proposal in comparison with previous literature is that we explicitly consider features of work organisation, such as the level of routine in the job (defined as repetitiveness and standardisation, and dealing with unforeseen circumstances as an additional element), separately from dimensions of task content such as the extent of physical strength or dexterity.

After presenting our taxonomy, in this paper we also introduced as illustrations three possible applications, all of which correspond to ongoing research. The first and most obvious application of our taxonomy is for measuring the task contents, methods and tools used at work in a given economy, drawing from new or existing surveys or occupational databases. A very preliminary analysis shows how this data cannot only be used for gaining a better understanding of what people do at work across different jobs, but also for classifying different types of labour input in a highly detailed way which is independent but complementary to the widely used classifications of occupation and sector. The second illustrative application we presented in this paper concerns the potential impact of AI on labour markets, an issue of increasing relevance in terms of policy and academic research. Our detailed taxonomy allows to map new AI applications to the specific tasks they may

affect, using the cognitive abilities required by the different tasks as an intermediate layer connecting them to AI applications. But our taxonomy can also be used to make the assessment more realistic, by taking also into account how work is organised in each particular case: the underlying assumption being that the more autonomy and teamwork, the less repetitiveness and standardisation entailed in each specific work process, the more difficult it will be to replace labour by machine input, independently of the (task-specific) technical feasibility of such an automation. Finally, we also briefly outlined how our taxonomy can be used to compare work in traditional labour markets and digital labour platforms, since the latter tends to be organised by task rather than by jobs.

The tasks approach has without any doubt been very fruitful for labour market analysis in the last couple of decades. But it has been too selective and partial in the identification of relevant task dimensions, and it has often neglected the social dimension of work and tasks organisation. In this paper, we have presented a taxonomy and conceptual framework that tries to overcome these limitations and contribute to the further development of this still very promising line of research.

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