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

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A 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 (Braverman, 1974), as well as from recent research on skills, work organisation and occupational change (see for instance Green, 2013; Cohen, 2016; Fernández-Macías and Hurley, 2017), in this paper we propose a new 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, artificial intelligence, digital labour platforms, Europe.

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Joint Research Centre & Eurofound (2019) - How computerisation is transforming jobs: Evidence from Eurofound's European Working Conditions Survey

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Introduction

In recent years there has been a flourishing of studies using a task-based approach to assess the employment effects of technological change. Adopting a conceptualisation of jobs as 'bundles of tasks', and assuming different automation suitability levels across the types of tasks performed by workers, some very influential papers have forecast that a considerable share of jobs could be at risk of automation[1] (or at least face significant changes in their content), although with a large variation across countries (see for instance Arntz et al., 2017; Nedelkoska and Quintini, 2018; Pouliakas, 2018).

A task-based perspective certainly enriches previous approaches to labour market dynamics by classifying jobs no longer on the basis of their generic skill endowment but according to the very object of potential substitution by machines and IT devices. However, there are important critical omissions in the relevant literature on task-biased technological change that deserve to be highlighted and addressed: on the one hand, the insufficient consideration of human agency as a key factor shaping tasks and production and service provision processes at the workplace-level; on the other, the lack of a proper account of the social and organisational aspects of production and service provision.

Building on a richer conceptualisation, and unlike most recent task-based contributions in economics, we propose a novel approach to the classification of tasks which goes beyond a purely technical and deterministic view of the production and service provision process. Jobs are not only bundles of tasks but also positions within the social structure of productive organisations, therefore sociological factors as the organisational set-up of production and service provision are key to understand the actual implications of technological change on employment.

In this paper, we propose a comprehensive and detailed taxonomy of tasks, going beyond existing broad classifications, and connecting the substantive content of work with its organisational context. In a nutshell, the taxonomy aims at answering exhaustively two key questions for understanding the impact of new technologies on work: firstly, what do people do at work? – i.e. the extent to which workers engage in specific physical, intellectual and/or social activities; secondly, how do they do their work? – i.e. the organisational structure of work. We also discuss the added value of our proposed taxonomy in assessing the employment impact of new technologies, by accounting for relevant ongoing transformations such as the diffusion of artificial intelligence and the unfolding of digital labour platforms.

The paper is organised as follows.

- We first provide a review of recent literature on job tasks and change in occupations, trying to identify several task categories that are relevant to characterise the nature of work activity (from an economic and social/organisational perspective).
- Based on this review, we then discuss what we believe are critical omissions in the literature.
- With the aim of filling the identified gaps, we then propose a new comprehensive and detailed taxonomy that differentiates on the one hand task content in terms of the object of work as transformative activity and on the other hand, the methods of work organisation and the tools used for work.

[1] Estimates are however much less pessimistic compared to other forecasting exercises based on occupations, rather than tasks within jobs, such as for instance Frey and Osborne (2013).

After presenting our taxonomy, we introduce as a way of illustration three possible applications for socio-economic research: first, to describe the distribution of employment in an economy across different types of task input; second, to assess the implications of recent AI developments for the labour market; and third, to bridge the regular labour market and the labour market of digital labour platforms.

We conclude the paper with a discussion of its added value, emphasising the contribution to the existing literature.

A review of recent literature on tasks and the changing labour demand

The polarization of the occupational structure, characterised by increasing employment in low and high-skilled jobs while decreasing for the middle ones, has been observed in several advanced economies in the recent decades. These developments were detected in countries such as the US and Germany in the 1990s (Autor, Katz and Kearney, 2006; Dustmann et. al., 2009), the UK since the 1970s (Goos and Manning, 2007), and Canada in the 1980s and 1990s (Green and Sand, 2015). However, as discussed in Fernández-Macías and Hurley (2017; see also Oesch and Piccitto 2019), job polarisation is not a pervasive phenomenon characterising all European economies in recent decades. Institutional and policy-related factors such as the deregulation of employment contracts or developments in minimum wage levels, for instance, can be associated with different levels of employment growth in the lower tiers of the labour market, and thus to whether job polarization or occupational upgrading is observed in a given country.

Most of the studies on this matter recognise recent technological change, in the form of information and communication technologies (ICT), as one of the main drivers of such asymmetric labour market developments. However, analytical approaches focusing on complementarities between technology and workers' skills, such as the popular Skills-Biased Technological Change (SBTC, hereafter) approach[2], were unable to offer satisfactory explanation of the polarisation of job growth. A novel approach focusing on the tasks performed by workers on the job, the very object of potential substitution by technology, was therefore put forward[3]. This is known as the 'Routine-Biased Technological Change' (RBTC, hereafter) approach, since it mainly classifies jobs according to their relative share of routine tasks rather than their generic skill endowment.

This "routinisation hypothesis" was first advanced by Autor, Levy and Murnane (2003) and argued that recent technological change, in the form of information and communication technologies diffusion, is biased towards replacing labour in routine tasks. Routine tasks, that are technically easier to codify and automate, can be either cognitive (such as record keeping or repetitive customer service) or manual (for instance repetitive assembly). Overall, four broad categories of workplace tasks are identified and classified along two main axes: routine (as opposed to non-routine) and cognitive (as opposed to manual). 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, polarising - rather than upskilling - trends can be detected in the data (see Acemoglu and Autor, 2011 for an exhaustive discussion).

Several influential papers defending the RBTC hypothesis and further investigating job polarisation draw on the Autor, Levy and Murnane model (see for instance Goos and Manning 2007; Autor, Katz and Kearney, 2006; Spitz-Oener, 2006; Goos, Manning and Salomons 2010; Autor and Handel, 2013). Autor, Katz and Kearney (2006) and Autor and Handel (2013) consider a three-fold classification of tasks by bringing together the two routine categories of Autor, Levy and Murnane (2003) in one. Thus, they classify 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, Manning and Salomons (2009, 2010) use instead the concept of service tasks, alongside abstract and routine, denoting those that involve social interaction with

[2] Proposed by Katz and Murphy (1992) and Katz (1999) and tested by (among the others) Berman et al. (1994) and Machin and Van Reenen (1998).

[3] Skills are defined as the stock of (innate or acquired) human capabilities that allow human beings to perform tasks (Autor, 2013, page 4). Different types of tasks require different types of skills, in quantitative and qualitative terms: some tasks require simple skills, some tasks require complex ones; some tasks require very specific and some tasks generic skills.

clients. Both manual and service tasks tend to be in the non-cognitive (low-skilled) and non-routine quadrant, and therefore would grow in relative terms with computerisation.

Cognitive (or abstract) tasks are often associated to formal educational requirements and refer to tasks that require intellectual effort (and therefore are complementary to information technologies). The definition of what constitutes cognitive tasks is not very precise in the papers reviewed, which sometimes can lead to contradictory measures. In the original formulation of Autor, Levy and Murnane, they further differentiated between analytical (information processing) and interactive (managerial) cognitive tasks: in our view, the introduction of managerial responsibilities in the measurement of this task dimension implies adding a dimension of organisational power that does not seem warranted by the underlying theoretical framework.

As could be expected, routine tasks are the focus of the model of RBTC and have been heavily studied in the recent literature. In the original formulation of Autor, Levy and Murnane, routine tasks are defined as those that “require methodical repetition of an unwavering procedure” (Autor, Levy and Murnane 2003, page 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 and Autor 2011, page 1076). A problem of this concept is that 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 carried out by F. W. Taylor and Henry Ford 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 depress labour demand in 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 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 and Hurley, 2017).

In addition to the strand of the literature which mainly focuses on the effect of technological change on employment, the increasing tendency towards the international fragmentation of production has stimulated a debate concerning the impact of offshoring on labour markets and production processes (see Bramucci et al., 2017 for a review). 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, 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 and Storper, 2001); can be summarised in deductive rules, and are therefore more routine (Levy and 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 emphasised in these studies as a key aspect of jobs to understand their offshorability.

Finally, a separate but also relevant strand of the literature discusses how recent organisational change affects labour demand, favoring some types of tasks more than others. Decentralisation of authority, delegation of responsibility and greater workers’ autonomy are among recent trends in work organisation according to this literature (see Caroli, 2001 and OECD, 1999 for a review). Indeed, these “new” forms of work organisation imply a shift from mass production, “Tayloristic” forms - characterised by centralised and bureaucratic control - towards “Just-in-Time”, flexible and less hierarchical ones, which increasingly rely on interaction, cooperation and exchange of information among workers; workers’ autonomy and responsibility, and decreasing task specialisation. A key message from this literature is “the hypothesis that modern organisational changes are complementary to skilled workers” (*Skills Biased Organisational Change*, see Caroli and Van Reenen 2001, p. 1450), and that technology can fully affect productivity and employment only when combined with a profound organisational change which is the necessary complement to innovation.

Some critical omissions of the task-based approach

According to the main proponent of the task approach in labour economics, tasks can be simply defined as units of work activity that produce actual output (Autor, 2013). Work is an input in the production process and tasks are discrete units of work which require specific skills (that is the stock of innate or acquired human capabilities) to be performed well. Different types of tasks require different types of skills, in quantitative and qualitative terms: some tasks require simple skills, some tasks require complex ones; some tasks require very specific and some tasks only generic skills.

Depending on the complexity of a given production or service provision process, this may require the combination of more or less different types of tasks, in the same way as it may require different types of raw materials. Therefore, the point of departure of this approach is a strictly technical view of the economy, seen as a mechanical process of transforming inputs into outputs.

It is worth noting the absence of any reference to human agency in the definition of tasks. This is intentional: one of the aims of the approach is to understand better the 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). Which factor will perform the 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, page 5). In other words, depending on what is technologically feasible, a task will be performed by the cheapest factor. Nevertheless, 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, page 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 – together with societal and cultural aspects that will be later discussed - 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 foundations at the micro level of the economy and it seems particularly useful for understanding the process of automation of some types of jobs, and the 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 human 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” as 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; Aghion 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' immiseration in early industrial capitalism to the active consent and trust searched by contemporary human resource practices (Heisig and 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[4] (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 very rarely exist in isolation, but are in the vast majority of cases coherently bundled into jobs.[5] 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 power, resources and life chances (Cohen, 2013, 2016; Grant et al., 2011; Parker et al., 2017). All these aspects also affect tasks in ways that are at least partly independent from technical considerations. For instance, the allocation of tasks to jobs is often the object of struggle between managers and workers, even collectively bargained (Cohen, 2016).

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

[4] The routinisation of industrial work was largely the result of this socially driven reorganization of production, although it is often discussed today as a purely technical attribute of industrial work. In our proposal, we consider routine as an aspect of work organization rather than task contents.

[5] 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 section 4, we discuss this issue with more detail.

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 taking into account 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.

A proposal for a comprehensive taxonomy of tasks

A review of the recent socio-economic literature on tasks has allowed us to identify several task categories that are relevant to characterise the nature of work activity and to understand recent developments of labour demand and structural change (for a more detailed review, see Fernández-Macías, Hurley and Bisello, 2016). The technological strand of the literature primarily focused on cognitive and routine tasks as the main dimensions, with other secondary task categories such as interactive (managerial), service and manual (as opposed to cognitive) also being considered. The literature on the effects of trade on labour demand, on the other hand, gives more emphasis to social interaction. The organisational literature, from another angle, emphasises the increasing importance of autonomy, communication and cooperation, and multitasking, as well as the interrelationship between technological and organisational change.

Our approach puts together the key elements stemming from the above-mentioned literature, while at the same time adding new dimensions to fill in what we consider to be important gaps. In an attempt to combine different streams of literature, 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 substantive content of work (i.e. extent to which workers engage different types of tasks) with the organisational structure of work (i.e. methods and tools used to do things).

Table 1 below presents our proposal for a taxonomy of tasks within jobs[6]. As a first step, tasks can be classified in two axes that are conceptually different: one which refers to the **content** of tasks (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.

[6] A previous version of the taxonomy was originally presented in Fernández-Macías, Hurley and Bisello (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:**
1. **Physical tasks:** aimed at the physical manipulation and transformation of material things: a. *Strength:* lifting people and heavy loads, exercising strength. b. *Dexterity:* precisely coordinated movements with hands or fingers. c. *Navigation:* moving objects or oneself in unstructured or changing spaces 2. **Intellectual tasks:** aimed at the manipulation and transformation of information and the active resolution of problems: a. *Information processing:* I. Visual and/or auditory processing of uncodified/unstructured information II. Processing of codified information i. Literacy: a. Business: read or write letters, memos, invoices,… b. Technical: read or write manuals, instructions, reports, forms,… c. Humanities: read or write articles or books. ii. Numeracy*:* a. Accounting: calculate prices, fractions, use calculators,… b. Analytic: prepare charts, use formulas or advanced maths b. *Problem solving:* I. Information gathering and evaluation. i. Information search and retrieval ii. Conceptualization, learning and abstraction II. Creativity and resolution i. Creativity ii. Planning 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.	1. **Methods:** forms of work organisation used in performing the tasks: *a. Autonomy* I. Latitude: ability to decide working time, task order, methods and speed. 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 *c. Routine* *I.* Repetitiveness*:* extent to which the worker has to repeat the same procedures *II.* Standardisation: extent to which work procedures and outputs are predefined and encoded in a formalised system III. Uncertainty (in reverse): extent to which the worker needs to respond to unforeseen situations 2. **Tools:** type of technology used at work: *a. Non-digital machinery (analog)* *b. Digitally-enabled machinery* I. Autonomous (robots) II. Non-autonomous 1. Computing devices a. Basic ICT (generic office applications) b. Advanced ICT (programming, admin) c. Specialised ICT *2.* Others

The content of tasks

The taxonomy of task contents is based on the object of work as transformative activity[7], the type of transformation involved, and on 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 essentially the approach of some recent very influential papers such as Frey and Osborne (2017), Arntz et al. (2017), 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 and people (although with variation in task complexity)[8]. 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:

- 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 involve precise movements with hands or fingers and corresponds most directly with the concept of manual tasks. As in the previous case, technological change has reduced significantly the amount of labour input in this kind of task for centuries: 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[9] (Wolbers and 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 expanded as technological change reduced the amount of human labour necessary to carry out physical tasks: but particularly in the case of information processing, advances in computing have allowed for a large-scale substitution of intellectual human input by

[7] The type of task content will tend to be associated to the economic sector to which the work activity belongs (for instance physical tasks are more typical of the primary and secondary, while social tasks are typically performed in the tertiary sector). However, the complexity of contemporary production and service provision processes means that there are all types of tasks in all types of sectors.

[8] 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.

[9] This is sometimes called "tacit knowledge" (see Polanyi, 1958 and 1966; Nelson and Winter, 1982).

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 uncodified/unstructured information, which as the previous category of "navigation" rely on complex low-level cognitive functions not completely understood, 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 codified 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:
    - 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[10.] As for intellectual tasks, the amount of labour performing this type of tasks content has grown as technological progress reduced the amount of physical tasks input needed: but unlike information processing, even the most advanced machines are still incapable of replacing humans for social interaction, so labour 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 between 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*: impart knowledge or instruct others.
- *Selling/influencing*: induce others to do or buy something, negotiate.
- *Managing/coordinatin*g: coordinate or supervise the behaviour of colleagues.
- *Caring*: provide for the welfare needs of others.

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

[10] Although this 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.

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" 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 (in reverse).
- *Teamwork*, which refers to whether or not carrying out their tasks in 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) [11].

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. As previously mentioned, Taylorism provides a good example: it was explicitly aimed at reducing work tasks to repetitive and standardised procedures in order to increase productivity, to gain a better control of the production process and to replace high by low-skilled labour input (Braverman, 1974). Of course, such a routinisation of work facilitated a later automation, but that is a different issue.[12]

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

- *Non-digital machinery*, that is, analog mechanical devices.
- *Digitally-enabled machinery*: either autonomous[13] digitally enabled machines (i.e. advanced robots), computing devices (differentiating by the level of skills they may require) or other digitally-enabled machinery.

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

[11] The more uncertainty in a work process, the more difficult it is to routinise it. This third sub-dimension of routine takes a different perspective and thus can improve its measurement by triangulation.

[12] For a discussion of routine-biased technical change, see Fernández-Macías and Hurley (2017). For a specific analysis of routinisation and computer use, see Bisello et al (2019).

[13] No technology, not even "autonomous" robots are fully autonomous, since they always require some human intervention. So the term autonomous machines here should be understood in a partial and relative, rather than absolute, way.

of digital labour platforms. In the three cases, the examples used refer to real research which is currently in progress.

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.

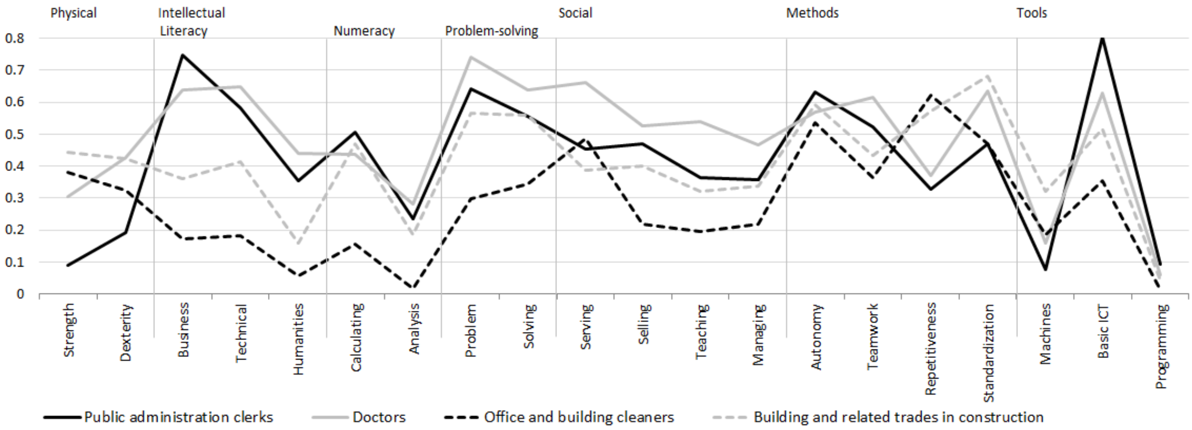

Figure 1: Task profile of 4 significant jobs, EU15 2014. Note: Employment shares in each job derived from the European Labour Force Survey data were used for weighting the indices.

For illustration, Figure 1 shows the distribution of task contents, methods and tools following the structure of our taxonomy in 4 relatively common jobs in EU15 countries on the basis of real data (Fernández-Macías, Hurley and Bisello, 2016). For each of the task categories, using surveys and occupational databases, data at the job level (2-digit occupation by 2-digit sector combinations) was compiled 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 Fernández-Macías et al (2016). According to this analysis, office and building cleaners carry out more physical than intellectual or social tasks, with a high degree of repetitiveness (though not so much standardisation) and limited use of machines or ICT; whereas public administration clerks carry out mostly business-related information processing tasks, with some problem-solving and a significant use of basic IT. Some task indicators are relatively high in the four occupations (problem-solving), while others are generally low (use of machinery, or analytic numeracy), and some are high in some cases and low in others (physical tasks and information processing). Physical and intellectual tasks are not always inversely correlated: for instance, doctors show high values for both physical and intellectual tasks; and a job typically physical as building trades involves relatively high levels of some types of intellectual tasks (such as technical literacy information processing or problem-solving). Social tasks are relatively widespread in the jobs shown in figure 1 (all jobs involve some degree of social interaction), but they also clearly differentiate categories of workers (selling and serving discriminate jobs which involve less or more direct contact with customers, for instance).

Task indices	Summary statistics		
In terms of the object of work/task:	**Mean**	**Std dev**	**CV**
1. Physical	0.28	0.11	0.39
a. Strength	0.25	0.13	0.52
b. Dexterity	0.32	0.10	0.33
2. Intellectual	0.49	0.11	0.22
a. Information processing	0.40	0.12	0.30
i. Literacy	0.47	0.12	0.26
-Business	0.55	0.24	0.44
-Technical	0.47	0.16	0.35
-Humanities	0.27	0.15	0.56
ii. Numeracy	0.34	0.13	0.39
-Accounting	0.48	0.23	0.47
-Analytic	0.21	0.16	0.74
b. Problem solving	0.57	0.11	0.20
i. Information gathering & evaluation	0.57	0.12	0.22
ii. Creativity	0.56	0.11	0.19
3. Social	0.40	0.10	0.26
-Serving/attending	0.46	0.12	0.26
-Selling/persuading	0.44	0.14	0.32
-Teaching	0.37	0.13	0.36
-Managing	0.34	0.11	0.33
In terms of the methods and tools used in the work/task			
1. Work organization			
a. Autonomy	0.58	0.12	0.21
b. Teamwork	0.48	0.20	0.41
c. Routine	0.49	0.13	0.25
i. Repetitiveness	0.41	0.16	0.39
ii. Standardization	0.58	0.17	0.30
2. Technology			
a. Machines	0.19	0.14	0.71
b. ICT	0.39	0.22	0.55
-Basic ICT	0.59	0.24	0.41
-Programming	0.08	0.10	1.20

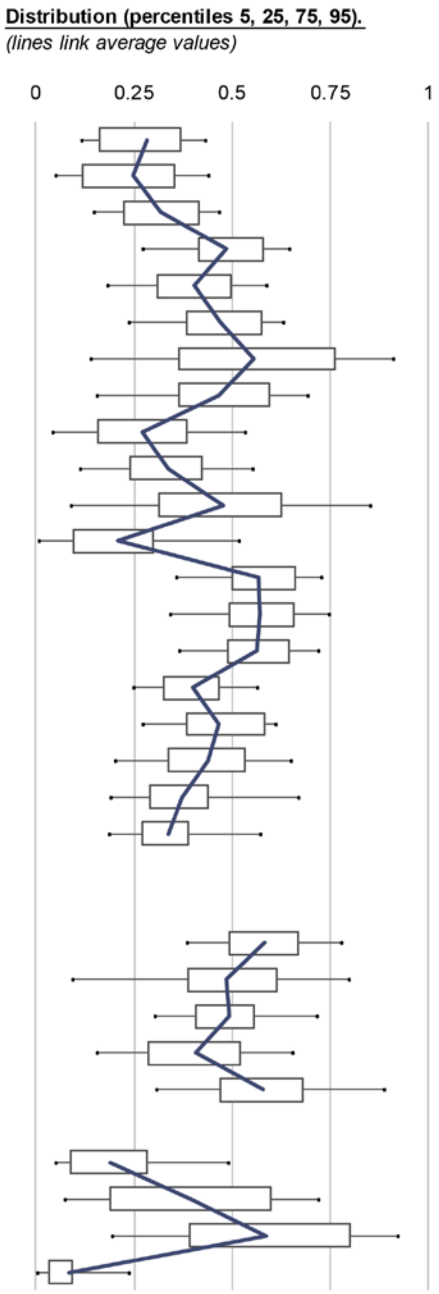

Figure 2: Average task scores for EU15, 2014. Note: Employment shares in each job derived from the European Labour Force Survey data were used for weighting the indices.

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 Figure 2. According to this approximation, the most frequent type of task content in European employment is intellectual, in particular business-type information processing and problem-solving, 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 tools are much more frequent than machinery. Figure 2 also shows the dispersion of values around the mean, which also varies significantly across task categories. Problem-solving, serving, selling and autonomy have high scores and a low dispersion, and are thus very widespread task types; whereas business-related intellectual tasks have high scores but high dispersion, suggesting a more polarised distribution.

Since some of the task indicators can be measured at the individual worker level, we can also use our approach to test empirically to what an extent occupations and sectors really capture distinct and internally consistent bundles of tasks as generally assumed. Table 2 shows a decomposition of variance across the task indicators available at the individual level, by subgroups of the working population defined by: 1) occupation only; 2) occupation and sector combined; 3) occupation, sector and country combined; and 4) country only.

	EWCS				PIAAC			
	ISCO	ISCOx NACE	ISCOx NACE Country	Country	ISCO	ISCOx NACE	ISCOx NACE Country	Country
In terms of the object of work								
1. Physical								
a. Strength	29.8%	33.8%	36.9%	4.0%				
b. Dexterity					8.2%	11.2%	18.0%	6.9%
2. Intellectual								
a. Information processing					35.8%	38.5%	40.9%	3.9%
i. Literacy					38.9%	41.2%	43.3%	4.2%
-Business					39.6%	40.7%	41.8%	2.6%
-Technical					23.7%	28.0%	32.6%	6.3%
-Humanities					31.8%	35.2%	36.1%	2.0%
ii. Numeracy					27.1%	31.1%	33.2%	2.7%
-Accounting					24.9%	29.2%	31.2%	2.4%
-Analytic					24.4%	28.3%	29.7%	2.0%
b. Problem solving								
i. Information gathering & evaluation	20.2%	24.6%	26.4%	3.4%	8.2%	13.3%	15.1%	2.4%
ii. Creativity	12.4%	15.4%	17.0%	2.2%				
3. Social								
-Serving/attending								
-Selling/persuading					22.3%	26.8%	28.4%	3.0%
-Teaching					28.6%	29.9%	33.5%	5.8%
-Managing					19.4%	36.2%	37.2%	2.5%
In terms of the methods and tools used								
1. Work organization								
a. Autonomy	16.2%	20.9%	24.1%	3.5%	17.8%	17.8%	17.8%	0.8%
b. Teamwork	5.3%	11.5%	13.1%	2.5%				
c. Routine								
i. Repetitiveness	12.0%	14.6%	18.6%	4.4%				
ii. Standardization	7.9%	11.6%	13.5%	2.2%				
2. Technology								
a. Machines	26.4%	30.2%	30.4%	0.4%				
b. ICT	45.8%	49.8%	52.0%	2.4%	51.3%	53.1%	53.6%	1.8%
-Basic ICT					36.6%	39.9%	40.0%	0.3%
-Programming					17.0%	21.9%	22.4%	0.4%

Table 2: Decomposition of variance at job and country level (for details, see Fernández-Macías, Hurley and Bisello, 2016)

The amount of individual variance in task content that can be explained by the occupation/sector combination ranges between 30% and 40% of the total in most cases. In other words, knowing someone's occupation, we can predict correctly between 30 and 40% of her task contents. This means that task content is strongly linked to occupational categories, but it also illustrates how a granular measurement of task content as the one proposed here can provide much more detail on what people do at work than the traditional occupation and sector classifications. Much of the variation in tasks takes place within occupations, either because the occupational classifications are not correctly reflecting the real patterns of division of labour and specialisation or because there is a significant degree of variation in actual task content even within occupational positions.[14]

Table 2 also shows that the variation in task methods is much less explained by occupation and sector than the variation in task content. Work organisation is much less determined than task contents by the material and technical characteristics of the production process, and thus its variation is much less related to occupation and sector. This illustrates the benefits of neatly separating the measurement of attributes of work organisation such as autonomy or routine from the measurement of task content such as manual dexterity or intellectual literacy, rather than mixing both aspects as in some of the literature reviewed in previous pages.

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 any new technology at the level of occupations is bound to fail. The effect of automation technologies on work is better understood at the level of specific tasks (Fernández-Macías et al., 2018).

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 type of 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 was in terms of numeracy and literacy information processing task content: again, either replacing labour input for the performance of some 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 very 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), speech and natural language processing 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 forthcoming paper, Tolan et al. (2019) 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[15], and the same list of human cognitive abilities can be also used to classify

[14] In fact, there is increasing evidence that the extent of task content within occupations is significant and often more important than the changes resulting from changes in the composition of employment by occupation (see for instance Freeman et al. 2020; also Bisello et al. 2019).

[15] 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 (Fernandez-Macias et al., 2018).

recent progress of the different domains of AI research.[16] 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[17] 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 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 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.[18]

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 incapable of 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. 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.

[16] In Tolan et al. (2019), 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).

[17] According to Tolan et al. (2019) this "deals with the perception of things, recognising patterns in different ways and manipulating them in physical or virtual environments with parts of the body (limbs) or other physical or virtual actuators, not only through various sensory and actuator modalities but in terms of mixing representations".

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

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. Jobs are more or less 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 are 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 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 traditional 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 traditional labour market and digital labour platforms. As illustrated in a previous section, using our taxonomy we can describe the traditional 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, most 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., 2109) would fit into one of the categories of the “intellectual” tasks of our index, either “visual processing of uncodified 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.

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 in mainstream economics the concept of tasks is relatively new, 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) or Karl Marx (who considered the task-biased effect of industrial technology to be deskilling), but the concept of tasks (and in general, any discussion of the production process as such) effectively disappears from mainstream economics with the marginal revolution. Neoclassical economics tended to ignore what happens within productive organisations, understood as black boxes that take skills, capital and raw materials as input and produce goods or services as outputs (Debreu, 1959: 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 epidemiology (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 and Hurley, 2017), in this paper we propose a new comprehensive taxonomy of tasks. This new 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 of 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 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 identify 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 examples three possible applications for it, 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 occupations and countries, 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. Indeed, we could even use this taxonomy to empirically test the degree of consistency in the distribution of tasks between occupations and sectors, showing that a bit less than half of the variation in task content is accounted for by 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 allow 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.

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