CEPS EXPLAINER

AI AT WORK

Why there's more to it than task automation

Laura Nurski

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Summary

To better understand AI's possible impact on jobs and employment, a task perspective is a good starting point – it provides insights into the automation potential of the current task content of occupations. However, it isn't sufficient for a holistic understanding because it ignores several important concepts that lie in between individual tasks and labour market outcomes. Jobs, processes and organisations mediate technology's impact on workers which is not captured by the task model of the labour market.

This CEPS Explainer provides a comprehensive framework for analysing AI's impact on work by moving through the concepts of tasks, jobs, processes and organisations. It highlights how AI is not only an automation or augmenting technology for productive tasks but it can also be used to better coordinate work and ensure the best people are hired. While the former might change the quantity of jobs and their task content, the latter two have a direct impact on job quality and inclusive access to work. Finally, it's the redesign of organisational processes surrounding AI's adoption that will ultimately shape the future of work.

Policymakers and other stakeholders are strongly encouraged to use the framework and glossary at the end of this Explainer to help foster a shared vocabulary and a holistic understanding of AI at work, as well as identify policy gaps and opportunities to proactively shape the future of work.

Dr. Laura Nurski is an Associate Research Fellow and Head of Programme on Future of Work at the Centre for European Policy Studies (CEPS). She is a quantitative social scientist holding a PhD in Economics, a M.Sc. of Advanced Studies in Economics, and a M.Sc. in Business Engineering (all from KU Leuven).

CEPS ▪ Place du Congrès 1 ▪ B-1000 Brussels ▪ Tel: (32.2) 229.39.11s ▪ Tel: (32.2) 229.39.11

Accelerating technological change and the changing nature of work are two of the main megatrends of our time. Ever since the seminal paper by Carl Frey and Michael Osborne, academics have tried to estimate the wider societal impact of general purpose technologies – like AI – on employment and jobs. Initially research focused on whole jobs – or, to put another way, which occupations would become extinct and which ones would remain. Since then, research has dived one step deeper into the task content of jobs – which tasks could be automated and which ones can't be. While this task approach is a good step forward, even this focus cannot fully capture the actual impact that AI could have on the future of work.

Thinking of jobs as bundles of tasks: AI for task automation

'AI will not replace entire occupations but it will change the task content of jobs'.

Policy, businesses and academia have embraced this line for thinking about AI's future impact on work and labour markets. The idea originates partly in the 'task approach' to labour markets. This labour economics model conceptualises jobs as bundles of tasks. These tasks come from a firm's production process that transforms inputs, such as raw materials, energy, labour and capital, into goods or services.

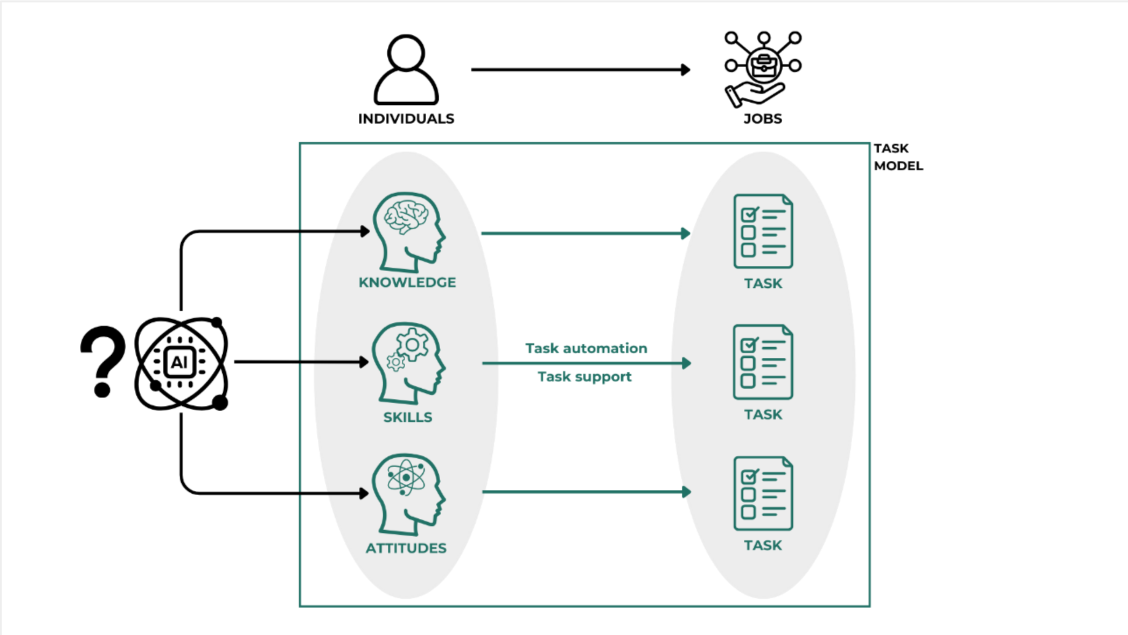
A transformative productive activity consists of a process of tasks. Tasks that require human capabilities are assigned to labour, while tasks that can be technologically and economically automated are assigned to machines. Technological change is then viewed as advancing the technological frontier, thus leading to more tasks being automated and creating new tasks for humans.

People are represented in this model as bundles of knowledge, skills and attitudes that together make up their competencies. Where skill refers to the ability to perform a specific task well, competence refers to the ability to easily undertake a group of similar or related tasks (known as a 'task domain'). People are then matched to jobs based on the fit between their competencies and the tasks that make up the job.

AI is quickly outperforming humans on abilities such as reading comprehension or visual question answering. Based on this technological potential, individual tasks or work-related abilities can be scored on their exposure to AI. Using occupational dictionaries with task descriptions, these task scores can then be used to calculate specific exposure scores for occupations, sectors, regions, and countries.

This framework has been the basis of several studies, including studies by the ILO, the IMF, the OECD, as well as multiple academic papers. While this model theoretically allows for the creation of new tasks, the empirical studies have been thus far been limited to the automation potential of current tasks.

Figure 1. Jobs as bundles of tasks



Source: Author's own depiction.

Some studies (see the hyperlinks in the paragraph directly below) have tried to further categorise occupations as exposed to either *automation* or *augmentation*, based on the share of tasks that are exposed to an automation technology. When many tasks in an occupation are exposed, the whole occupation is labelled as 'automation-exposed'. If an occupation consists of both automatable and non-automatable tasks, like teaching, then the occupation is said to be exposed to augmentation instead.

This is sometimes also referred to as 'shielded from automation' due to non-automatable bottleneck tasks. However, shielding from automation can also arise from social aversion to automating certain professions, for example judges – their function and work at the centre of a society's legal and justice system is simply seen as too important to automate.

Other studies distinguish automating from augmenting by analysing whether technologies target occupations' specific *task inputs* (automation) or *outputs* (augmentation). For example, a patent for a 'method of strengthening and repairing fingernails' would complement the work of fingernail technicians but wouldn't replace them. A patent for a 'wash-and-wear coat' on the other hand would instead make laundry and dry-cleaning workers completely obsolete.

While this works at the occupational level, the conceptual distinction between automation and augmentation is not as clearcut at the task level.

This is because a task can often be split into smaller subtasks. Consider a bundle of tasks where some of them (*A*) can be automated while others (*B*) cannot be automated. When *A* tasks are automated, a worker will finish more *B* tasks in the same amount of time it previously took to do *A* and *B* together. As a result, that worker will be more 'productive' at completing all their previously assigned tasks together (*A*+*B*) but not necessarily more productive at completing the non-automatable tasks (*B*).

This reveals that a worker's productivity depends on the bundling of tasks that make up a job. Yet within occupations there can still be considerable differences in a job task bundle. Occupational dictionaries with task descriptions thus overly simplify a reality that is actually more richly captured by worker surveys. The existence of these task differences within occupations already points to the fact that task bundling isn't a fixed or deterministic feature of the labour market. Instead, it's the result of choices made by organisations, departments and teams.

When a job consists of only a few tasks, then it's much easier to replace a worker with full automation. In the case of AI, such full automation usually requires traditional supervised machine learning applications that are trained to perform a specific task and are sometimes embedded within physical robotic systems. Think, for example, about quality control in manufacturing using computer vision to detect defective or non-compliant products. First a camera is used to capture images of the products; then an algorithm decides whether they're of a high enough quality; and finally, a robotic arm pushes the non-compliant product off the production line.

The new generation of generative AI systems have so far not yet led to full task automation. Instead, these large language models (LLM) have mainly supported humans with their tasks, rather than replaced humans completely. There have been task-level productivity gains in the double digits due to generative AI support in coding, writing, customer service and consulting. These applications consist of AI assistants or *co-pilots* that can suggest code, different types of text, answers to customer complaints, new product ideas and even full strategic marketing or data analysis plans.

Studies on writing and consulting have included analyses on lower-level subtasks and have highlighted how task support or augmentation at the overall task level could be considered as 'automating' a subtask (*A*), so that the sum of the subtasks (*A*+*B*) can be performed quicker. In the case of writing, for example, less time goes to brainstorming and rough drafting (*A*), while more time goes to editing (*B*) but *A* and *B* together are jointly performed much faster.

Consistently these studies find that lower-skilled or less experienced workers gain the most from such AI task support. The gains in speed and quality are highest for those who performed slower or worse in their tasks before AI support became available. The reason is obvious when considering how an LLM is trained. While annotating and labelling data for finetuning AI models is usually a low-skill task, the original data itself (see the coding and customer service examples below) is often generated by people who have a certain level of expertise.

In the case of coding, training data is captured from coding websites such as StackOverflow as well as functional bits of code in public code repositories. Activity on StackOverlow has been decreasing since the introduction of ChatGPT, meaning that less expert training data is being generated. In the case of customer support, the AI is trained on previous customer support chats that were labelled as successful, thus ensuring that it learns only from the best-performing support agents.

This means that the tacit knowledge of experienced coders, writers, support agents and consultants is captured by the LLM and helps less experienced workers reach the same level of output speed and quality. Some authors thus argue that this will make previously high-skilled jobs more accessible to middle-skilled workers.

Finally, a 'jagged technological frontier' is emerging from this task-level research, meaning that AI support doesn't benefit all cognitive tasks equally – and potentially even harms some of them. In the consulting example, humans benefitted from AI support in a creative task but not in an analytical task. Similarly, legal students benefited from AI support in a multiple-choice exam but not in an essay-based exam.

The task approach has generated some insights into the potential impact of AI on jobs. *First*, few jobs turn out to be completely automatable, due to the presence of non-automatable tasks, meaning these jobs will likely experience changing task content rather than complete automation. *Second*, several tasks such as coding, writing, customer support and consulting can be performed much faster due to being supported by generative AI. *Third*, not all tasks benefit equally from this support – some tasks might even be harmed by it – pointing to a jagged technological frontier. *Finally*, lower-skilled and less experienced workers gain most from AI support, possibly making some high-skilled jobs more accessible to a wider group of people.

THINKING OF TASKS AS PARTS OF A PROCESS: AI FOR ALGORITHMIC COORDINATION

The task-based perspective described above allows for a comprehensive assessment of the automation potential of a range of tasks in the economy. However, this perspective is limited because it considers tasks individually without considering the larger systems that they're a part of. The task model conceptualises jobs as bundles of tasks and whether they're automatable or not, independently of the other tasks. As this is a simplification of reality, a task-based approach isn't sufficient to analyse AI's impact on work. Expanding the task-based model in several directions gives us more clues on what AI's potential impact could be.

A first expansion is that tasks are not independent from each other but, in fact, are interdependent parts of larger processes. Such interdependence between tasks requires coordinating the actions of the people executing them. Tasks can be interdependent across time (when one can only start after the other is completed), across methods (when the method used in one task depends on the method that was used in the other) and across resources (when the two tasks make use of one shared resource, like a machine or a set budget).

When interdependent tasks are done by one and the same person, coordination across the tasks can be handled by this one person's autonomous decision-making. A small independent entrepreneur, for example, usually manages their own planning, methods and resources across all their projects and clients. Cross-human coordination is only needed when the interdependent tasks are being done by multiple people.

When interdependent tasks are held by multiple people, organisations create coordination mechanisms to align their actions. While the transformative tasks are part of the *production process*, coordinating tasks are thus part of the *governance process*.

WHEN INTERDEPENDENT TASKS ARE HELD BY MULTIPLE PEOPLE, ORGANISATIONS CREATE COORDINATION MECHANISMS TO ALIGN THEIR ACTIONS. WHILE THE TRANSFORMATIVE TASKS ARE PART OF THE *PRODUCTION PROCESS*, COORDINATING TASKS ARE THUS PART OF THE *GOVERNANCE PROCESS*.

The European Commission's Joint Research Centre has therefore extended the technical task framework to include not only production tasks (i.e. *what* people do at work) but also coordinating tasks (i.e. *how* people do what they do). The coordination methods they include are autonomy, teamwork and routine. While autonomy supports the coordination of tasks done by one person, as explained above, teamwork and routine are coordination methods for tasks done by multiple people.

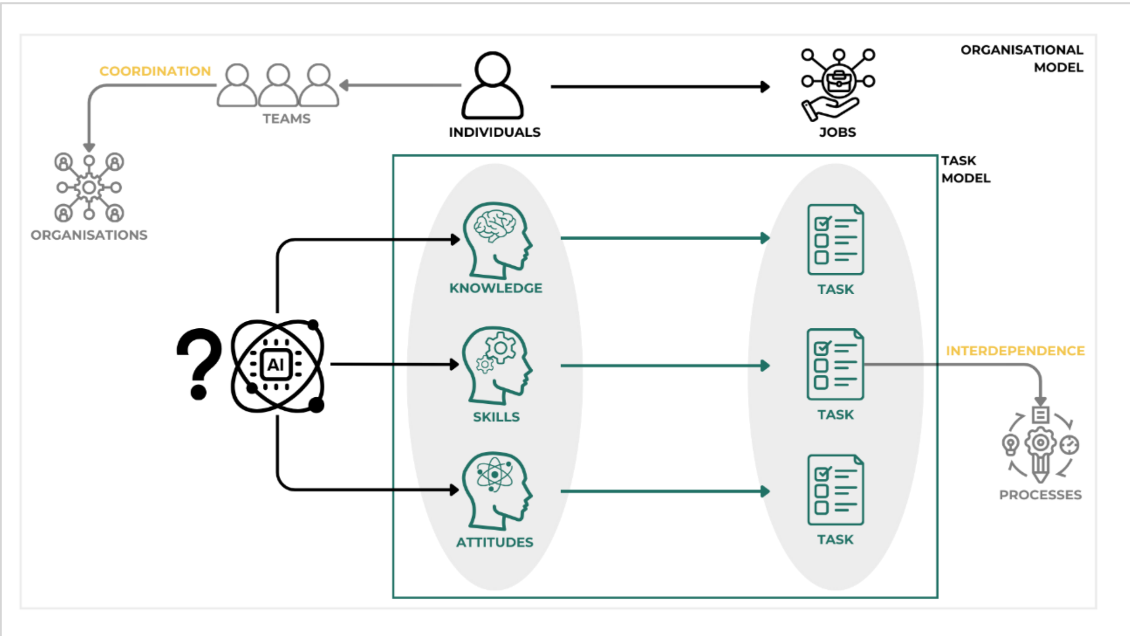
In a stable and predictable production process, task coordination can be standardised trough organisational routines and procedures and doesn't need much human coordination at all. Routineness is a major predictor of earlier computer automation, as computers are especially suited to handle routine cognitive tasks.

Remaining coordination needs can usually be handled through the hierarchical decision chains across functionally specialised departments. In extreme cases, when coordination is very simple and transaction costs are low, such tasks can be outsourced to the market and coordination happens through contracts or online labour platforms. However, in a highly uncertain and unpredictable production process, coordination is best handled by responsive humans within organisational structures that closely surround the process, such as through end-to-end teams.

Understanding the interdependence between tasks is thus crucial for successful organisation design. Effective organisational structures lead to efficient coordination but also provide room for workers to adapt to changes and respond to new information. This leads both to more productive processes as well as richer, more complex jobs for workers.

Organisation design is thus a shaping force in the bundling of tasks in jobs, both horizontally (the production tasks) and vertically (the coordination tasks or governance methods). Through both channels, *how* an organisation is designed also shapes workers' automation exposure.

Figure 2. Tasks as interdependent parts of processes



Source: Author's own depiction.

Task interdependence also matters for successful technology adoption. When technology automates a certain task, organisations must also rethink the coordination across the automated task and the next human task in the process.

Consider, for example, the coordination between a radiologist and a surgeon in a hospital. Both jobs are complex and their tasks are highly interdependent – the surgeon operates on the patient based on the radiologist's diagnosis. However, the coordination across their tasks is standardised in most cases, namely through the radiologist delivering a textual and visual report to the surgeon.

Previous machine learning-based image recognition research focussed on performing a diagnosis from medical images. However, more recent research has explored the use of LLMs for reporting a diagnosis to physicians, thus automating the coordination between the radiologist and the surgeon. Again, this would not necessarily automate away the radiologist's job but it would allow them to spend more in-person time on the cases that require more intense coordination with the surgeon.

Using algorithms in task coordination is a form of algorithmic management called *algorithmic operational management* (AOM) as it manages operational activities. Given the interdependence identified across time, methods and resources, algorithmic use cases can be found in scheduling and planning, work instructions and resource allocation. Examples include algorithms for just-in-time scheduling based on historical patterns and real-time data, for giving work instructions through AR glasses or other smart devices, and for allocating rides to drivers on online platforms such as Uber.

Using AOM in the example of the radiologist and surgeon is more supportive than directive – the surgeon still has a lot of autonomy and isn't constrained by the LLM's decision. More directive AOM use cases risk harming the quality of work with potential losses in autonomy, decreased skill use or increased work intensification.

In terms of the canonical workplace wellbeing model in organisational psychology (the Job Demands-Resources model), AOM risks increasing job demands while reducing job resources. Or, in terms of another popular model, Self-Determination theory, AOM risks harming basic psychological needs such as autonomy, competence and relatedness or belonging.

While these risks are not inherent in the technology *per se*, empirical evidence shows that job quality effects tend to be more negative for the more directive (vs the more supportive) use cases of AOM. Strengthening workers' voices and codetermination when adopting new technologies helps to mitigate these effects.

While lacking in the EU's AI Act, the Platform Work Directive provides information and consultation rights for workers on the algorithms that are used to manage them – but crucially it only applies to workers in the platform economy.

This section sheds a first light on why the simple task framework introduced earlier is insufficient to assess AI's impact on work. *First*, the task content of occupations is neither exogenous nor deterministic but is shaped by organisation design. *Second*, the interdependence between tasks puts a limit on how far a task can be automated, at least until the coordination across tasks is reconsidered. *Third*, using AI to coordinate tasks across people could pose a risk to job quality.

THINKING OF ORGANISATIONS AS BUNDLES OF PEOPLE: ALGORITHMIC HR MANAGEMENT

We need to expand the task model a second time as organisations serve another function beyond merely coordinating tasks across people. They also place people into jobs based on the expected or assessed fit between their competencies and the job's task requirements.

People are placed into jobs through a collection of human resources management (HRM) processes. These include both the initial recruitment and selection of a new person (hiring), moving or reallocating existing employees to new functions (evaluation and promotion), removing employees (termination) and the upskilling of employees (learning and development).

All these functions determine *who* gets a job within the organisation but also what kind of position they get in the overall hierarchy, what kind of privileges and opportunities they receive, and what career options are made available to them.

HR processes are thus crucial when it comes to inclusivity and equal opportunities at work. These processes are also impacted by much uncertainty around the future performance of candidates or employees. There are ongoing efforts to support HR professionals with AI in these processes. Use cases include AI for CV screening and analysing video interviews, for workforce skills intelligence, and for individualised training programmes. Using AI to support these HR processes constitutes another form of algorithmic management. To distinguish it from algorithmic operational management (AOM), this form is called *algorithmic HR management* (AHRM).

> **WHEN HISTORICAL HR PROCESSES ARE BIASED TOWARDS CERTAIN DEMOGRAPHIC GROUPS, THEN THE DATA USED TO TRAIN HR ALGORITHMS WILL BE BIASED AS WELL. IN SHORT, IF UNCHECKED, THE ALGORITHMS WILL EXHIBIT THE SAME TYPE OF DISCRIMINATORY BEHAVIOUR AS THE HUMANS THAT TRAINED IT.**

The two types of algorithmic management have very different implications and risks. The risk of AOM was situated mostly in terms of a job's quality. The risk with AHRM is whether AI will select or deselect people into jobs fairly and whether it will favour certain groups of people. When historical HR processes are biased towards certain demographic groups, then the data used to train HR algorithms will be biased as well. In short, if unchecked, the algorithms will exhibit the same type of discriminatory behaviour as the humans that trained it.

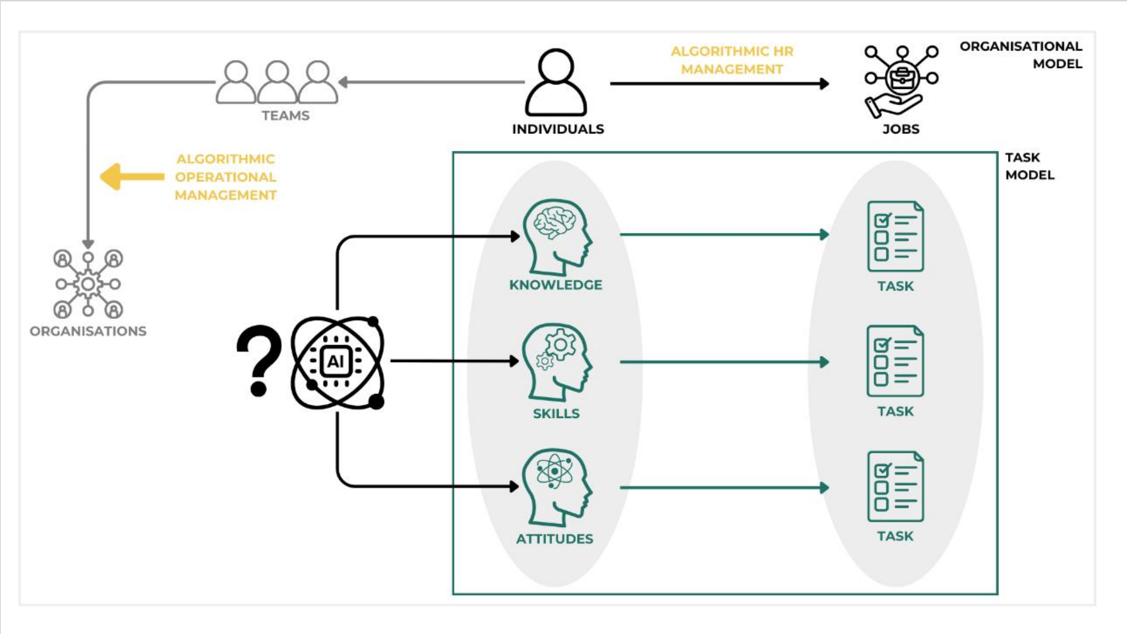
The bias that can arise in such systems has been extensively documented. They can be biased against women in CV screening or against people of colour in facial recognition for security checks. The fact that AI reveals previously less visible human discrimination could also be considered an opportunity. The AI Act rightfully imposes that these high-risk applications are trained on representative datasets and that bias detection systems are put in place.

Incidentally, AHRM also changes the task content of HR professionals' jobs. This usually happens with the extensive digitalisation of HR processes. AI needs data to run, namely the data on both the candidates and employees that are being assessed but also the behavioural data of the HR professional themself.

While there could be large productivity gains in HR, there's also a risk of increased proceduralising and monitoring of HR processes. This would result in reduced autonomy, less human interaction and thus less job satisfaction/meaningfulness for the HR professional. This joint development of automating tasks and generating information about the process ('automate and informate') has been identified as a unique ICT feature that distinguishes it from earlier technologies. AI is no different in this sense.

> This section offers a *fourth* perspective that is missing from the task model – that AI can change the labour market by influencing how people are placed into jobs, as well as employees' organisational positions. Consequently, this could redistribute the wages, privileges and career options of particular demographic groups.

Figure 3. Organisations as bundles of people



Source: Author's own depiction.

Thinking of organisations as goal setters: AI for system redesign solutions

The model is complete when we consider that processes of interdependent tasks are designed to achieve a desired outcome. Indeed, organisations are groups of people who work together towards a shared goal. When taking this systems perspective, it becomes clear that the aforementioned AI applications in either the production process (task automation) or the governance process (AOM and AHRM) are only point solutions.

A point solution is when a technology is applied in one element of a system while keeping the other elements constant. An example would be swapping out the steam engine in a 19th century factory with a newly developed electric motor but keeping the factory's system and machinery layout around the central engine the same. Marginal productivity gains may be realised from such point solutions, for example through a more reliable energy supply. However, large gains are unlikely to arise from such partial solutions.

System solutions, meanwhile, start from the desired outcome (or the identified problem that needs to be solved) and use technology to redesign the *entire* system and its processes. During the Second Industrial Revolution, such system redesign happened when electric motors began to be used to power each machine individually (a unit drive) instead of centrally powering all the machines at once (the older central drive). Switching to the unit drive caused a complete reconfiguration of the factory floor, eventually leading to the first assembly lines and the mass production of the early 20th century.

Other examples of system solutions include electric street lighting, lifts and car washes which did not arrive through meticulous one-by-one task automation but rather through reconfiguring the whole environment where the technology operates.

As the above examples show, throughout history it has always been system solutions supported by general purpose technologies (e.g. steam, electricity, computers) that have generated the largest productivity gains. But it takes considerable time between inventing a new general-purpose technology and redesigning production systems to make optimal use of them.

While the electric motor was invented and improved upon throughout the 19th century, the first assembly lines only appeared in 1913. In short, the technology was available but both public infrastructure and business processes weren't reconfigured around them for decades afterwards. Similarly, the productivity paradox of the 1970s and 1980s – when the arrival of computers didn't immediately lead to increased productivity – kickstarted the business process reengineering efforts of the 1990s that reconfigured organisational processes to make optimal use of the new ICT technologies.

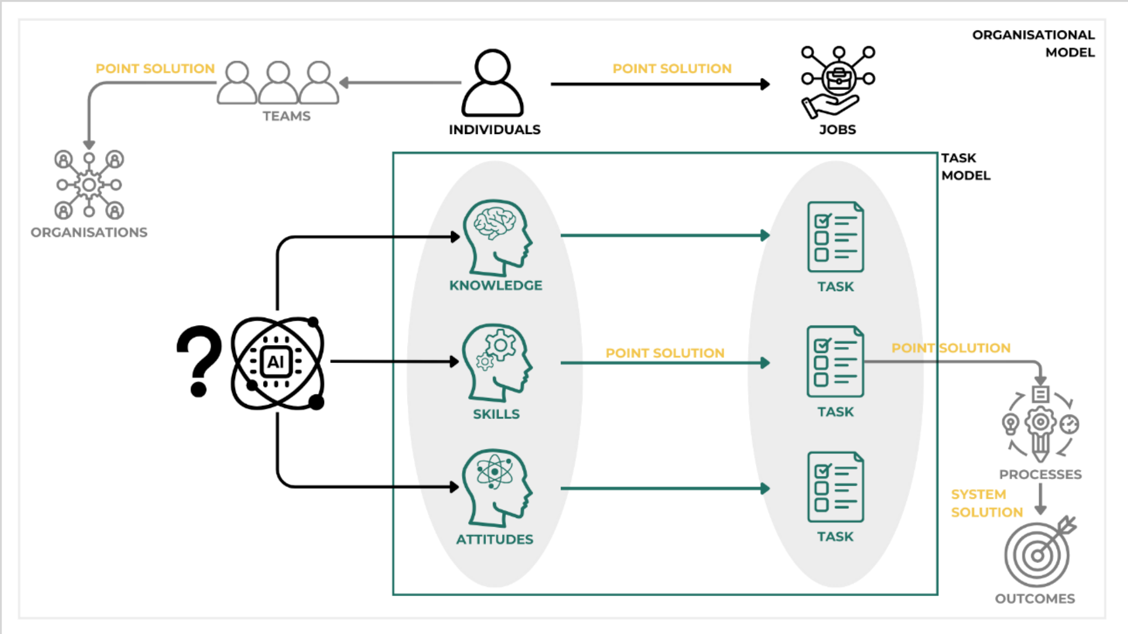
When it comes to AI, we're currently in this 'in-between time' where technology adoption is starting to take off but social systems surrounding them still need to be reconfigured to make the best use of them. To reach the other side of the in-between time, we need to figure out how to redesign our production and governance systems to optimally use AI.

Some early indications that this is (slowly) starting to happen can be found in the development of AI-driven system solutions for specific organisational subsystems. Take for example maintenance in industrial production. The goal of maintenance is to ensure that machinery continues to function and to fix malfunctioning equipment as quickly as possible, thus avoiding production downtime.

Instead of automating existing maintenance processes step-by-step, for example by building a maintenance robot, AI has supported a new way of preventing downtime, namely through predictive and preventative maintenance. These types of maintenance use historical and real-time usage data to predict when a machine is likely to fail so that human technicians can intervene before it happens. While a maintenance robot might work a little faster or longer hours than a human, predictive and preventative maintenance is where the real productivity gains lie, even without any job losses.

Identifying the areas where AI can support system or subsystem redesign for greater productivity or reduced human pressure is the challenge that organisations are facing today. Digitalising organisational processes has both generated a lot of data and has proceduralised many professions. These data-rich routine processes that create large administrative burdens, for example in education and healthcare, might be worth investigating further.

Figure 4. Organisations as systems



Source: Author's own depiction.

The *fifth* and final perspective that is missing from the task automation model is the system redesign perspective. Technology can do more than simply automate existing processes task-by-task. It can also be used to support new ways of achieving a system's ultimate goal, by creating new processes that increase productivity and generate new human tasks along the way.

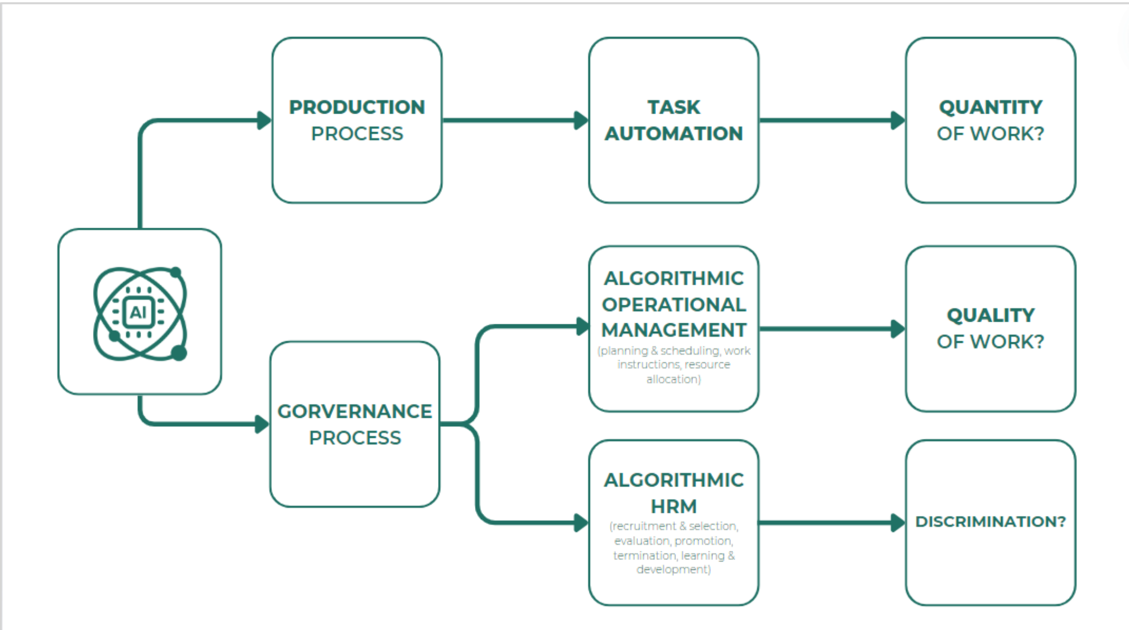
CONCLUSIONS – AND WHERE EU POLICY CAN LEND A HELPING HAND

AI can automate certain human tasks or make humans more productive at undertaking those tasks. Tasks and workers that were previously thought to be safe from automation are now considered at risk and in need of reskilling. This task perspective has fuelled a lot of research on how far various occupations, sectors and regions are at risk of automation. This research mostly deals with the question of how many jobs will be left over in the future – and which types of skills will be needed to do them.

However, as shown throughout this CEPS Explainer, there is much more to AI and the future of work than mere task automation.

AI isn't just a technology that can be used in the production process but given its decision-making capabilities, it can also be applied to how organisations are governed. It can coordinate tasks across workers – operational management – and it can select people into jobs – HR management. The main risks associated with these applications are not so much in the quantity of jobs, but more in the *quality* of jobs and discrimination.

Figure 5. Summary of AI applications in workplaces and their risks



Source: Author's own depiction.

Existing EU policies only partially address some of these risks. Algorithmic management is regulated in the proposed Platform Work Directive but only for workers in the platform economy. The AI Act does recognise HR processes as a high-risk area, meaning that high quality datasets will be required to minimise discriminatory outcomes in these applications. When it comes to the changing task content of jobs, EU policy focusses mainly on supporting skills development (e.g. through the European Skills Agenda) and improving labour mobility.

TO HELP COMPANIES BETTER UNDERSTAND THE JAGGED TECHNOLOGICAL FRONTIER, POLICYMAKERS COULD PROVIDE A FRAMEWORK FOR SAFELY EXPERIMENTING WITH AI IN SPECIFIC TASKS – AND SHARE LESSONS LEARNED ACROSS THE EU.

The above policies react to the risks stemming from AI point solutions (task automation and algorithmic management). However, the EU could play a role in proactively (re)directing point solutions and even support the development of AI-driven system solutions as well. Through R&D and innovation policies, it could help to steer technological progress towards human-complementary technologies, especially in sectors where the market doesn't provide those incentives. To help companies better understand the jagged technological frontier, policymakers could provide a framework for safely experimenting with AI in specific tasks – and share lessons learned across the EU.

Finally, given the importance of redesigning social systems alongside the adoption of new technologies, policies could also support the experimentation and collaborative development of joint technological and social innovation. This could take place both within research programmes like Horizon Europe and social investment programmes like ESF+. It would require sectoral expertise (to understand the desired outcome), multidisciplinary design disciplines (to understand the interdependence in the system) and 'Living Labs' for open innovation in real-life environments.

AI AND THE FUTURE OF WORK – A GLOSSARY

Through this CEPS Explainer, we hope that taking the reader through the framework of tasks, jobs, processes and organisations has helped to shed clarity in their thinking about the (ever evolving) impact of AI on work and the labour market.

To stimulate dialogue among stakeholders and policymakers, and to foster a shared vocabulary, this Explainer leaves the reader with a glossary of key terms to guide them forward.

Glossary

- Algorithmic management: The use of AI organisational processes to manage both work and workers.
  - Algorithmic HR management (AHRM): The use of AI in HR processes such as recruitment, selection, evaluation, promotion, termination, and learning and development.
  - Algorithmic operational management (AOM): The use of AI in managerial processes to coordinate tasks across people.
- Automation: The use of technology to replace labour with capital.
- Augmentation (or task support): The use of technology to make workers more productive in a given task.
- Competence: The bundle of knowledge, skills and attitudes that support the ability to perform well in a group of similar or related tasks.
- Coordination: Aligning the execution of one task with another to achieve the optimal joint outcome.
- Jagged technological frontier: The uneven suitability of tasks to benefit from AI support.
- Job: A grouping of tasks assigned to a worker, along with a set position within the organisational structure.
- Occupation: A construct that groups jobs in the labour market together based on similarities in tasks and organisational positions.
- Process: A sequence of steps to achieve an outcome.
  - Production process: A sequence of steps to transform raw materials, energy, labour and capital into finished goods or services.
  - Governance process: A sequence of steps to align people's actions within an organisation.
- Skill: The ability to perform a specific task well.
- Task: A step in the productive transformative process.
- Task interdependence: The degree and nature (time, methods or resources) to which tasks rely on each other to be completed.

CEPS
Place du Congres 1
B-1000 Brussels