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Article

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The Design of Digital Automation Technologies: Implications for the Future of Work*

KEY MESSAGES

- **Automation technologies, including within the same family, are fundamentally heterogeneous in their design and the tasks they can execute**
- **While the number of sectors that are exposed to most digital automation technologies is still relatively limited, it is expanding**
- **Data-intensive technologies are more pervasive in services than in manufacturing sector**
- **This calls for policy to extend its focus from robots to other, more pervasive, forms of automation**
- **Robots are designed more to substitute workers than to complement them, while data-intensive technologies are consistently more complementary to humans**

Contemporary discussions about automation and employment echo a long history of labor-saving technologies. This history has unfolded in waves of disruption to existing labor practices and has been accompanied by anxieties (Mokyr et al. 2015). These used to decline as new occupations were created and economic growth continued to raise the demand for labor, albeit in very different jobs than those that were lost or disrupted. The history of automation anxiety has been constellated by a succession of claims that "this time it will be different." Digital, following mechanical and electrical automations, is no exception.

However, such a claim requires empirical assessment. First, an assessment of emerging capabilities for technologies such as robotics and AI to automate tasks is needed. The hype of attention that these two technologies, of all others, are attracting seems to be due to the proclivity of humans to anthropomorphize such devices – so a robot arm or a decision-making AI algorithm receives greater attention than an automated measuring system for filling containers, though in all these cases there are implications for human labor.

A second consideration is the nature of jobs. Job classifications often reduce the complexity of the tasks that workers do within their activities. In many cases, deploying labor-saving devices results in the reconfiguration of tasks rather than elimination of jobs, so that the net impact on jobs is complex and difficult to ascertain a priori – it often requires ex post assessment and greater precision in identifying emerging capabilities.

The novelty of this study with respect to extant reviews of the literature on the labor impacts of automation is in the purposefully sought classification of different automation technologies, digging in-depth into their technical design and specific capabilities to carry out tasks, and the assessment of these capabilities to substitute or complement workers.

In sum, this study performs a systematic review of the literature from engineering and technology that broadly addresses the following research questions:

a) Are digital automation technologies designed to substitute, complement, and/or reconfigure specific tasks executed by humans within sectors?
b) What are these specific tasks across sectors? Are they specific to some sectors? To what extent can they be routinized?

We first glance over the history of technical progress that led to automating labor processes. We offer a (re)designed classification of digital automation technology families. We then systematically review the technical literature focusing on Robotization, Artificial Intelligence, Data Acquisition, and Data Management, and look at how these technologies are designed for different sectors and tasks, to substitute or complement humans while routinizing tasks.

AUTOMATION TECHNOLOGIES AND EMPLOYMENT: A BRIEF HISTORY

The history of labor-saving innovation is constellated by a continuing development of the past waves of automation. Mechanization continues to develop and is influenced by electrification, while digitalization influences both previous waves. The interactive and

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cumulative effects are important. For example, early mechanization was driven by steam power, which dictated that plants would be vertically organized due to the constraints in distributing motive power horizontally. With electrification, the organization of factories, and the nature of jobs, were transformed first by the extension and development of horizontal "assembly lines" and, more recently, by different "work station" and "machine cluster" groupings.

The 20th century is a history of industrial mass production displacing craft production, in which the individual worker executed a variety of operations, from fabricating to finishing a product. More recently, mass production has been extended to operations in service industries such as processing payments in banks, or the surgical operating theatre. In many services, there are residual craft elements that continue to rely on the skill of the "operator," though in some cases, the logic of mass production has been reversed so that the customer becomes the operator and the service is "co-produced" (Savona and Steinmueller 2013).

Technological history shows that processes of automation involving mechanization and electrification have been underway for an extended time. In many cases, labor-saving innovations have greatly improved individual worker productivity, and most of the job losses in global North manufacturing have already occurred as a result. Digitalization, combined with international logistics and transport, has continued this process. Digital automation has greatly improved the ability to codify designs, communicate about production issues, trace and monitor transport of parts and partially finished goods, and efficiently manage inventories in relation to the flow of production and consumption.

The technological potentials of newer generations of cyber-physical systems have the potential to further transform the mass production paradigm.

A great deal of uncertainty arises regarding the role of emerging digital automation in replacing service-sector jobs. For example, the historical occupation of data entry operator has experienced dramatic reductions as automation of data acquisition displaces centralized facilities for data entry and filing and replaces them with a "data cloud." This, in turn, offers opportunities for the application of machine-learning AI to create predictive models and manage data-intensive service provision. In many of these cases, the challenge is to improve the human-computer interface so that opportunities, choices, and services can be customized to the users' needs. The flexibility and scalability of robotic equipment has major implications for employment in "customer-facing" jobs, with a customer now facing a cyber-physical system rather than a human being. Assessing the potential for the emerging new wave of automation, and whether "this time it will be different," begins with a careful assessment of the emergence of capabilities in the cyber-physical systems that are the current subjects of research, development, and initial deployment.

EMERGING DIGITAL AUTOMATION TECHNOLOGIES AND EMPLOYMENT: A GRANULAR VIEW

We have identified eight families of digital automation technologies (Ciarli et al. 2022):

- Robots – technologies that sense and (autonomously) act based on data
- Physical data acquisition technologies – technologies that harvest and record information
- Software-based data management – technologies for storing, protecting, managing/handling and acquiring data
- Computing – technologies used to compute/calculate
- AI (not directly as a cloud service) and Intelligent Information Systems – technologies using algorithms and advanced methods to make sense out of the data
- Additive manufacturing (using any material – such as powder metallurgy as well as bioplastic filament) – technologies that produce bottom-up based on digital models

– Networking – technologies for communicating between machines (data transmission) or connecting machines
– User interface – technologies for human interaction with machines or data.

What is relevant in this context is not only the heterogeneity of the emerging digital automation technologies, but also that of the affected aspects of employment. This study reviews the literature from engineering and technology based on a systematic screening and coding (illustrated in Ciarli et al. 2022) and extracts the following information about the technology-employment nexus.[1]

Tasks design
– Routinization: technologies execute functions at the level of single operations or activities, with different degrees of autonomy. Automation depends on how much tasks or sub-tasks can be routinized (and the relevant knowledge for them to be executed codified), how single operations can be separated or consolidated, and the ability to perform a task without any or different degrees of human intervention (e.g., supervision).
– Knowledge codification: technologies can be executed through explicit codified instructions or based on tacit knowledge. Tacit know-how is a cornerstone of the economics of knowledge (Cowan et al. 2000; Foray and Steinmueller 2003) and so far has been exclusively considered a domain of human action.

Employment compensation
Complement or substitute: technologies can complement or replace human labor, having a productivity or substitution effect (Acemoglu and Restrepo 2019). We not only consider automation as complementary or as a substitute for workers, but also how the specific technical design replaces and/or complements segments of tasks (or sub-tasks) across different sectors.

For each of the technology families identified above, we built a query that captures the technology, the tasks carried out, and the applications. We selected the most-cited papers and screened them for relevance, that is whether the paper discusses design, prototypes and early implementation of technologies within the given family, and applications that execute specific tasks and services. Finally, we coded all relevant papers along the technology-employment dimensions described above. Specifically, we used NACE Rev 2 to allocate papers to a sector, and Broad Work Activities from O*NET to categorize tasks. We coded 154 papers for robots, 122 for software-based data management, 259 for AI, and 192 for physical data acquisition technologies.

[1] Ciarli et al. (2022) consider other features, such as exposure, level of adoption, maturity of the technology, time-saving or process innovation, and geographical location of the technology implementation.

DIGITAL AUTOMATION: TASKS, COMPLEMENTARITY AND SECTORAL EXPOSURE

Tasks within Work Activities and Complementarity with Humans

Table 1 shows the shares of papers describing, for each technology family, the tasks they were designed to execute across and within each O*NET broad work activity reported in column 1 (columns 2–5), and the share of papers that describe how they complement rather than substitute human workers (columns 6–9). Work activities are ranked in descending order by Robots, Software-based data management (DM), AI and Physical data acquisition technologies (DA).

The four technologies differ substantially in the tasks they are designed to execute, particularly between robots and the three data technologies. Around 50 percent of the papers mention that robots carry out tasks related to “Handling and moving objects” or “Identifying objects, actions, and events.” Technologies pertaining to the data value chain of DA, DM, and AI are similar to each other with respect to the work activities they carry out, but there are important differences also among those.

For instance, a substantial number of papers in AI refer to “Identifying objects, actions, and events,” and “Estimating the quantifiable characteristics of products, events, or information” (hardly mentioned by papers in DA and DM), but only a few discuss technologies for “Getting information,” which instead are widespread among papers discussing DA and DM technologies. The highest share of sampled papers describes how these technologies carry our tasks of “Processing information” for DM, “Analyzing data” for AI and a less complex or analytic task such as “Monitoring processes and materials” for DA.

None of the digital automation technologies seem (up to 2021) to be executing tasks implying interactions with people from “Coaching and developing others” to the management of human resources (in the bottom part of the columns in red.)

A low share of robot technologies mentioned in at least 5 percent of the coded papers are designed to complement humans. Around 50 percent of the coded papers mention that robots that carry out tasks related to “Handling and moving objects” or “Identifying objects, actions, and events” will complement workers.

Most of the remaining papers discuss activities designed to replace workers, with a small share (approx. 15 percent) designed to both complement and substitute workers – for instance in the case of automation that requires human supervision. Only a small share (20–30 percent) of papers on robots unveils a design that complements human workers for tasks

Table 1
Share of Papers Describing Sector of Adoption, Process Improvement and Routinization of Working Activities by Technology Family (Ranked by R)

Tasks	Shares of papers by work activity				Complementing workers			
	Robots	DM	AI	DA	Robots	DM	AI	DA
Handling and moving objects	23%	0%	0%	0%	46%	0%	0%	0%
Identifying objects, actions, and events	18%	2%	18%	9%	58%	100%	84%	73%
Performing general physical activities	9%	1%	0%	0%	30%	100%	0%	0%
Getting information	9%	16%	3%	11%	46%	92%	95%	86%
Assisting and caring for others	6%	0%	0%	0%	58%	0%	0%	0%
Inspecting equipment, structures, or material	6%	1%	1%	6%	20%	100%	100%	64%
Controlling machines and processes	5%	0%	0%	1%	19%	100%	0%	80%
Operating vehicles, mechanized devices, or equipment	4%	0%	0%	0%	21%	0%	0%	0%
Monitor processes, materials, or surroundings	4%	5%	7%	27%	31%	70%	90%	75%
Analyzing data or information	3%	20%	26%	14%	42%	87%	93%	89%
Processing information	2%	29%	15%	17%	25%	91%	85%	80%
Interpreting the meaning of information for others	2%	1%	1%	0%	29%	67%	50%	0%
Training and teaching others	1%	0%	0%	0%	0%	0%	33%	0%
Documenting/recording information	1%	5%	0%	3%	40%	92%	100%	82%
Making decisions and solving problems	1%	3%	3%	1%	40%	69%	68%	43%
Judging the qualities of things, services, or people	1%	2%	5%	0%	25%	100%	67%	50%
Organizing, planning, and prioritizing work	1%	1%	0%	0%	0%	50%	0%	0%
Communicating with supervisors, peers, or subordinates	1%	1%	0%	0%	100%	100%	0%	0%
Developing bjectives and strategies	1%	0%	0%	0%	0%	0%	100%	0%
Scheduling work and activities	1%	7%	0%	0%	0%	66%	33%	100%
Interacting with computers	0%	1%	0%	0%	0%	80%	0%	0%
Performing administrative activities	0%	0%	0%	0%	0%	100%	100%	0%
Provide consultation and advice to others	0%	0%	0%	0%	0%	100%	0%	0%
Monitoring and controlling resources	0%	2%	1%	2%	100%	36%	100%	75%
Evaluating information to determine compliance with standards	0%	1%	3%	3%	0%	33%	100%	92%
Estimating the quantifiable characteristics of products, events, or information	0%	0%	14%	5%	100%	100%	95%	72%
Coaching and developing others	0%	0%	0%	0%	100%	0%	100%	0%
Performing for or working directly with the public	0%	0%	0%	0%	0%	0%	0%	0%
Establishing and maintaining interpersonal relationships	0%	0%	0%	0%	100%	0%	0%	0%
Selling or influencing others	0%	0%	0%	0%	0%	100%	100%	0%
Staffing organizational units	0%	0%	0%	0%	0%	0%	0%	0%
Updating and using relevant knowledge	0%	0%	0%	1%	0%	0%	100%	100%
Communicating with persons outside organization	0%	0%	0%	0%	0%	0%	0%	0%
Guiding, directing, and motivating subordinates	0%	0%	0%	0%	0%	0%	0%	0%
Repairing and maintaining mechanical equipment	0%	0%	0%	0%	0%	0%	0%	0%
Resolving conflicts and negotiating with others	0%	0%	0%	0%	0%	0%	0%	0%
Thinking creatively	0%	0%	0%	0%	0%	0%	0%	0%
NA	1%	0%	0%	0%	0%	0%	100%	0%
Total papers	445	441	717	762	178	373	629	597

Notes: The table reports the share of papers that were coded as describing industries related to each NACE sector (column 1), for each of the following families of technologies: Robots (2), Software-based data management (3), AI (not directly as a cloud service) & Intelligent Information Systems (4), and Physical data acquisition technologies (5). Columns 6–9 report the share of papers, for each technology family and sector, which suggest that the technology improves the efficiency in producing the good/service, as opposed to improving their quality. Columns 10–13 report the share of papers, for each technology family and sector, which suggest that the technology allows to routinize the task on which they focus. The final row reports the total number of papers that were coded in relation to each sector: one paper can refer to more than one sector; therefore, the number of work activities is larger than the number of papers.

Source: Authors' compilation.

such as "Controlling machines and processes" or "Performing general physical activities." In the case of "Controlling machines and processes," however, 50 percent of the papers mention both complementing and substituting, while in the case of "Performing general physical activities" the combination of complementing and substituting is mentioned in only approximately 15 percent of the papers.

Overall, this suggests that different cohorts of robots with different degrees of capabilities co-exist, with some only improving efficiency and facilitating workers' operation, while others fully automate processes, for example by opening the way for flexible factory-floors with reconfigurable assembly systems.

Unlike robots, around 80–90 percent of the papers that discuss DM, AI, and DA suggest that these data-intensive technologies complement human workers in all main work activities that they carry out, such as "Analyzing data or information," "Processing information," and "Getting information." There are some exceptions, such as DA technologies related to "Inspecting equipment, structures, or material": only 60percent of the papers suggest that DA may complement workers, with the remaining share of the papers suggesting substitution, as in the data filler operator example mentioned above.

In sum, the data value chain technologies (Acquisition, Management, and AI) share a high degree of complementarity with humans, which are the repository of the tacit knowledge needed to complement automated and routinized data acquisition and processing. Human knowledge and activities in these tasks acts as an enabler or, better, as an essential factor – without it, the task cannot be executed at a sufficient level of efficiency granted by automation technologies or is not valuable.

Sectoral Exposure, Process Innovation and Routinization

Table 2 shows the share of papers that discuss technologies related to specific sectors for each technology family (columns 2–5) and, within each sector, the share of papers that discuss technologies that improve efficiency, as opposed to those that improve the quality of the good/service (columns 6–9), or routinize activities (columns 10–13). Sectors are ranked in descending order with respect to the share of papers by robots, DM, AI, and DA.

Considering the sectors mentioned in at least 5percent of the publications, the academic literature focuses on a few, recurrent sectors across technologies. While different technology families apply to several work activities, they are all relevant only for a small subset of sectors. The most common across technologies is "Professional, scientific, and technical activities (M)." This feeds R&D activities that allow prototypes, technical design, and subsequent deployment. Beyond "Professional, scientific, and technical activities (M)," there are important differences across technology families. While robots focus on "Manufacturing (C)," tasks related to "Analyzing data or information," carried out by DM, AI, and DA, are discussed in relation to "Information and communication (J)," "Human health and social work activities (Q)," and to a smaller extent, "Manufacturing (C)" and "Agriculture, forestry, and fishing (A)." The sector focus is similar also for tasks related to "Processing information," carried out by DM, AI, and DA. Highly intensive and creative services do not seem to be the focus of papers concentrating on DA, DM, and AI.

There are large differences in the technologies: we find a larger focus on improving efficiency in AI and DA papers, while Robots and DM place a stronger focus on improving the product or service. Interestingly, a considerable share of papers describes AI and DA as improving processes and routinizing tasks in most personal services (Accommodation and food (I) Administrative support (N), Real estate (N), and Finance (K)), which are the most pervasively exposed to data-intensive technologies. Despite the differences in relation to complementing labor, it is interesting to note that robots and DM technologies have a lower tendency to mention the routinization of activities than AI and DA. This suggests that, although they do not substitute workers, these technologies are able to make these tasks highly replicable.

POLICY CONCLUSIONS

This study reviewed a large sample of core academic papers from engineering and technology disciplines, which present and discuss four digital automation technologies that execute tasks across different industries. This provides an understanding of how the technical design of digital automation technologies that have been emerging since the early 2000s may affect different aspects of employment, according to the technology developers. We summarize the key messages below.

First, automation technologies, including within the same family, are fundamentally heterogeneous in their design and the tasks they can execute. These tasks tend to be specific to one sector, but often extend to several sectors (such as analyzing data or information).

Second, the number of sectors that attract the development of most digital automation technologies is still relatively limited but expanding. From this type of work, policymakers can form expectations about what occupations and industries are more likely to be affected by digital automation technologies in the future.

Third, data-intensive technologies, particularly DM, but also AI and DA, are more pervasive in services than in manufacturing sectors, which calls for policy to extend its focus from robots to other, more pervasive, forms of automation.

Table 1

Share of Papers Describing Tasks within Work Activities by Technology Family and Degree of Complementarity with Human Workers (Ranked by R)

		Shares of papers by sector				Process improvement				Routinisation of activities			
Group	Labels	Robots	DM	AI	DA	Robots	DM	AI	DA	Robots	DM	AI	DA
M	Professional, scientific and technical activities	24%	35%	20%	41%	40%	34%	95%	92%	33%	42%	89%	90%
C	Manufacturing	34%	15%	11%	14%	61%	42%	95%	87%	71%	33%	98%	80%
A	Agriculture, forestry and fishing	7%	3%	3%	12%	52%	57%	100%	96%	100%	29%	67%	76%
Q	Human health and social work activities	9%	3%	35%	10%	58%	60%	99%	70%	68%	80%	83%	85%
J	Information and communication	1%	22%	7%	8%	0%	48%	83%	91%	50%	76%	96%	87%
F	Construction	2%	5%	6%	4%	9%	27%	100%	74%	46%	50%	95%	87%
T	Activities of households as employers	1%	2%	1%	3%	100%	0%	100%	85%	67%	50%	100%	92%
I	Accommodation and food service activities	2%	0%	0%	2%	38%	0%	100%	86%	100%	0%	100%	86%
N	Administrative and support service activities	5%	3%	1%	2%	46%	0%	100%	85%	64%	77%	100%	85%
E	Water supply; sewerage, waste management and remediation activities	2%	1%	4%	2%	86%	100%	100%	100%	86%	0%	94%	100%
H	Transportation and storage	4%	2%	2%	1%	59%	60%	81%	100%	59%	70%	94%	82%
D	Electricity, gas, steam and air conditioning supply	1%	2%	3%	0%	75%	20%	100%	100%	0%	70%	100%	100%
S	Other service activities	4%	1%	0%	0%	47%	0%	100%	100%	65%	100%	100%	100%
B	Mining and quarrying	2%	1%	2%	0%	90%	100%	100%	100%	60%	0%	100%	100%
L	Real estate activities	0%	0%	0%	0%	0%	100%	100%	100%	0%	100%	100%	100%
K	Financial and insurance activities	0%	2%	2%	0%	0%	22%	100%	0%	0%	22%	87%	0%
P	Education	0%	0%	1%	0%	0%	0%	56%	0%	0%	0%	89%	0%
O	Public administration and defence; compulsory social security	0%	2%	1%	0%	0%	0%	100%	0%	0%	43%	100%	0%
R	Arts, entertainment and recreation	1%	0%	0%	0%	50%	0%	100%	0%	17%	0%	100%	0%
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%
U	Activities of extraterritorial organisations and bodies	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
NA		2%	0%	0%	0%	11%	100%	0%	0%	22%	50%	0%	0%
Total papers		445	441	717	762	230	171	682	671	267	227	640	654

Notes: the table reports the share of papers that were coded as describing tasks related to each of the O*NET broad work activities under column (1), for each of the following families of technologies: Robots (2), Software- based data management (3), AI (not directly as a cloud service) & Intelligent Information System (4) and Physical data acquisition technologies (5). The last four columns report the share of papers for each technology family and work activity, which suggest that the technology complements workers. The final row reports the total number of papers that were coded in relation to each work activity: one paper can refer to more than one work activity, therefore the number of work activities is larger than the number of papers.

Source: Authors' compilation.

Fourth, the literature on robots shows, however, that they are designed more to substitute workers than to complement them, while so far data-intensive technologies are consistently more complementary to tasks performed by humans. As it turns out, this is driven by the type of service produced, which is an input to other activities, rather than by the inability of routinising tasks, which is also higher for data-intensive technologies.

Fifth, the future of work depends on how technologies will evolve, their idiosyncrasies, their stage of development and adoption, and the specific tasks they complement or replace within the most-exposed sectors (Ciarli et al. 2021). Labor market policies should rely on evidence on digital automation at a greater level of granularity to be properly informed about their heterogeneous effects on task reconfiguration within sectors.

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