Working Paper
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Ready, but challenged:

Diffusion and use of artificial intelligence and robotics in Danish firms

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Abstract

This working paper explores the diffusion and effects of artificial intelligence and robotics on work organization and skills formation in Danish private and public companies. The main focus is on how humans and technology interact, the extent to which employees have the skills to engage in this interaction, and the interplay between job content and technology. The main findings are the following: Artificial intelligence is more diffused and diffuses more rapidly than robotics, and this diffusion is uneven across Danish regions; Danish employees are very confident in using artificial intelligence and robotics, but half of the employees lack the necessary skills; skills are to an important extent acquired through on-the-job learning, which are insufficient in the long run; artificial intelligence involves a larger variety of learning than robotics and has a greater impact on tasks and work organization. The working paper concludes with recommendations for policy and management. Important recommendations are that there is a need for policy makers to focus on developing new formal education and training and to innovate existing education in order to ready current and future employees for technological change, and that management needs to focus more on continuous development of their human capital. Lifelong learning and strategic human resource management become increasingly important.

Keywords: AI, robotics, sociotechnical system, skills, work organization.

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1. Executive summary

The present working paper explores the diffusion and effects of artificial intelligence and robotics on work organization and skills formation in Danish private and public companies. The main focus is on

- how humans and technology interact,
- the extent to which employees have the skills to engage in this interaction,
- the interplay between job content and technology.

Five main findings appear in the present working paper.

- Artificial intelligence is more diffused than robotics and diffuses more rapidly.
- There is an uneven diffusion of artificial intelligence and robotics across Denmark. The technology is more diffused in Eastern Denmark and in regional capital cities.
- Danish employees are very confident in using artificial intelligence and robotics. However, only half of the employees feel that they have the necessary skills.
- Skills are to an important extent acquired through on-the-job learning, which will be insufficient in the long run for securing that employees have the necessary skills. Policy makers and management need to focus more on developing formal training and education, and make sure that formal training and education is implemented through work place practices and on-the-job learning.
- Artificial intelligence involves a larger diversity of learning than robotics, and it impacts more tasks than robotics. This means that artificial intelligence affects work organization to a larger extent than robotics. In effect, implementing artificial intelligence is more challenging for management than robotics.

There are many ways of organizing work with artificial intelligence and robotics. We argue that firms can differentiate themselves from other firms in the way in which they combine humans and technology. Different combinations may exist within the same firm, and it is likely that the ability to create different combinations within the same firm becomes a source of competitive advantage.

New types of jobs are gradually appearing, and a number of current types of jobs will disappear. Especially middle-range skilled jobs may be affected. There is a need for policy makers to focus on developing new formal education and training and to innovate existing education in order to ready current and future employees for technological change. There is a need for management to focus more on continuous development of their human capital. Lifelong learning and strategic human resource management become increasingly important.

The uneven diffusion of artificial intelligence and robotics across the Danish regions may call for concern. Policy makers need to contemplate policy schemes that promote technology diffusion in peripheral areas.

2. Introduction

In late February, a fortnight before the world was struck by Corona lockdown, Josh Dzieza asked in a feature on the internet media *The Verge* "How hard will the robots make us work?" (Dzieza, 2020). Reflecting on recent work practices in a number of American retail corporations including Amazon and Google, the main message of the feature was that the deployment of artificial intelligence and robotics deteriorates work conditions in terms of higher work pace and more stress. The misery occurs, because people are managed by automated systems that take dehumanising Fordism to its next stage, including supervision of work pace, assessment of professionalism at work, and surveillance of social interaction among workers.

This is a grim picture of the role that human capital plays in automated or semi-automated environments, and it calls for concern about the effects on working conditions caused by robotics and artificial intelligence. However, the picture is to some extent contested by research pointing to the opportunities which artificial intelligence and robotics imply for job enrichment and the creation of new jobs. Surveying studies on the impact on the number and content of jobs, Frontier Economics argues that job losses will occur in types of jobs where low levels of skills and/or non-complex interaction with other people prevail, and that job creation will mainly appear in types of jobs that support and complement the use of artificial intelligence and robotics, evaluate and judge the output, and create the conditions within which artificial intelligence and robotics operate (Frontier Economics, 2018). This will favour the need for upskilling of the workforce and, in some job roles, autonomy and learning opportunities. In a recent report (World Economic Forum, 2020a), World Economic Forum points to the creation of a wide range of new job types that will emerge in the near future, implying the need for accommodating new skills requirements at rapidly changing labour markets. While the portfolio of skills requirements differ substantially across the new job types which are identified, the common denominator is the high-skilled ability to create, engage, interpret, judge, and act upon data and activities involving artificial intelligence and robotics.[1]

While the public discourse on artificial intelligence and robotics is mainly positive in terms of promises for upskilling, growth, and welfare, these promises are still in the making, and it is important to remember that positive effects of technological progress do not occur by themselves, but require human agency (Caruso, 2018). The way in which work is organized and leadership applied is important to the impact of artificial intelligence and robotics, especially regarding work content and working conditions. Workers may be substituted by new technology, or the application of new technology may be complemented by changes in work content. What happens depends on how job content and technological development are combined, and this implies that the effects of artificial intelligence and robotics do not necessarily follow a predestined path, but are shaped by managerial intent and decision making. As explained by Nielsen, Lorenz and

[1] The opening up of new opportunities alongside the displacement of certain types of jobs associated with artificial intelligence and robotics may lead to increasing inequality in terms of job opportunities and earnings. While this is an issue that calls for major concern, it is, however, outside the scope of this working paper.

Holm in a forthcoming contribution (Nielsen et al., 2021), the way in which artificial intelligence and robotics are implemented is sensitive to how management creates opportunities for upskilling and development of new competencies, and how employees embrace and accommodate to these opportunities.[2] In a similar vein, Neuburger and Fiedler (2020) point out that there is a potential for dehumanization as well as empowerment and inclusion, and within this continuum the actual effects of implementing artificial intelligence and robotics depend on how the socio-technical system is composed and thus how humans and technology co-exist. The needs for IT skills, skills in machine-human interaction, problem-solving skills, skills in organizing own work, and the exercise of social skills in interaction with colleagues are all shaped by this implementation. In most cases, the actual socio-technical system will be located at some point at the continuum between dehumanization and empowerment.

During recent years, the implementation of artificial intelligence and robotics has been associated with the evolution of Industry 4.0, which is mostly described as a new technological paradigm. The term Industry 4.0 was coined by a German initiative for industrial policy aimed at developing and utilizing a wide range of new opportunities based on how the Internet-of-Things (IoT) allows for new methods of communication and collaboration among technology, humans, and value chains.[3] IoT enables machines to communicate and collaborate with machines, and systems with systems, without human interference, and it enables new ways of communication and collaboration among machines and humans, e.g. in the form of activities in virtual reality. Machines and systems can undertake decentralized decision making based on artificial intelligence, robots can substitute human labour to a higher extent than before, and new technologies such as 3D print and prototyping in virtual reality radically change existing activity systems and value chains. Data on products, processes, and quality can be integrated across companies throughout the value chain, providing enhanced opportunities for just-in-time and build-to-demand production systems. In its most extreme form, Industry 4.0 will lead to completely automated cyber-physical systems that operate without human beings, but we are yet a long way off from achieving this promise.

Within research on Industry 4.0, the implementation of artificial intelligence and robotics is often discussed in terms of how prepared the organization is for such implementation. To some extent, being prepared is associated with maturity for adopting new technology, e.g. models for digitalization or smart manufacturing. A number of maturity models have been developed in order to distinguish between different levels of maturity, ranging from three to seven dimensions that to some extent can be associated with

[2] Nielsen et al. (2021) point to the fact that there are relatively few studies on this issue. Among others, they refer to Dauth et al. (2017), and to Bessen, et al. (2019).

[3] Most of the literature on Industry 4.0 assumes that we have experienced three prior paradigms since the industrial revolution-hence the use of ”4.0”. Industry 1.0 is associated with the evolution of mechanization powered by steam and water during the 18-19th century, which in the 19-20th century was replaced by Industry 2.0 in terms of electricity-powered machinery integrated in mass production targeting mass consumption markets. During the 20th century, Industry 3.0 developed in the form of automation based on electronics and IT, and now Industry 4.0 is emerging as intelligent production based on IoT, cloud technology, and big data. A thorough account of this development and the wide array of new technologies is given by Oztemel, & Gursev (2020). Examples of how Industry 4.0 technologies are implemented across a large variety of industries can be studied in Frank et al., (2019). How Industry 4.0 is treated within a large number of social science disciplines is analysed in an extensive literature survey by Erro-Garcés, (2019).

different types of organizational maturity.[4] The concept of maturity can also be applied at the macro level, e.g. by focussing on a country's composition of industries and the associated potential for automation[5], or by analysing the extent to which the IT infrastructure of a country is conducive to Industry 4.0 practices[6].

This working paper relies on the data from the 2019 TASK survey (see box 1). It delves into the diffusion of artificial intelligence and robotics in Denmark and its effects on work organization and skills, including the extent to which the Danish work force lacks the skills needed for operating in an artificial intelligence and robotics working environment. In doing so, it gives an impression of how socio-technical dimensions have evolved during 2016-2019 and the current status of technology-human interaction in the field. Based on the reflections that we have presented above, it is expected that Denmark as an Industry 4.0 frontrunner is characterized by work organizational arrangements and skills formation that are conducive to the exploitation of artificial intelligence and robotics. This involves a certain amount of employee discretion in problem solving and an increasing degree of complexity embedded in the task environment, causing demands on problem solving skills and social interaction. While these trends are observed in the following account, we also notice that the observed trends differ across high and low skilled employees, and that there is a need for investing in human capital. As the use of artificial intelligence and robotics is maturing in the Danish economy, human capital formation becomes critical to the way in which socio-technical systems are build, especially if there is a managerial intent to avoid dehumanization of the work force. We conclude the working paper by identifying a number of areas for policy intervention to that effect.

In the following, section 3 digs into the diffusion of artificial intelligence and robotics and shows that artificial intelligence is more diffused than robotics, diffuses more rapidly, and that the eastern part of Denmark is taking a lead in this development. Sections 4 and 5 discuss the effects on, respectively, skills and work organization. Section 4 shows that Danish employees are very confident in using artificial intelligence and robotics, and that the use of artificial intelligence requires a broader range of types of learning than robotics. Section 5 points to jobs in Danish firms as being predominantly complex, empowering, and requiring self-reliance among employees, and that artificial intelligence has a broader impact on job content than robotics. Section 6 points out that half of the Danish employees lack skills for the future use of artificial intelligence and robotics and calls for a more prominent role of formal training and education. Finally, section 7 presents a number of policy recommendations.

[4] A brief overview is presented by Mittal et al. (2018). The authors suggest a model with five archetypes, i.e. novice, beginner, learner, intermediate, and expert.
[5] An example of this can be found in the previously mentioned Frontier Economics (2018), pp. 34-37.
[6] An extensive analysis exemplifying this approach can be found in Castelo-Branco et al., (2019). They conclude that the Scandinavian countries with Finland as a leader are frontrunners on Industry 4.0 readiness.

Box 1: The TASK survey

The Technology and Skills (TASK) survey was initiated in 2018 as part of a research project funded by the Aalborg University Social Science Talent Programme for Younger Researchers. Additional funding was obtained through the ReDy project, which was funded by the Obel Family Foundation. The TASK questionnaire was developed over 2018 with inspiration from Eurofound's European Working Conditions Survey (EWCS) and OECD's Programme for the International Assessment of Adult Competences (PIAAC) survey to ensure comparability. Unique questions on the use of technology at work were also developed for TASK. The data collection process was outsourced to Statistics Denmark, who ran a pilot in late 2018. The final TASK data were then collected by Statistics Denmark in the first half of 2019. Statistics Denmark constructed the sample from census level registry data on both firms and employees, and stratified the sample by region and size of workplace from the registries. They also supply post-stratification weights created from the registry data. The survey had a response rate of 39.9 percent and the final dataset consists of 1244 observations

Appendix 1 contains the full tables of the survey, and appendix 2 contains further details on the methods used for collecting the data

3. Diffusion of artificial intelligence and robotics

In this section we show that artificial intelligence is more diffused than robotics, and it diffuses more rapidly. To some extent, this difference may be caused by the composition of the Danish economy, which is an economy dominated by services rather than production. Furthermore, artificial intelligence and robotics are comparatively more used in the eastern part of Denmark. The main provincial capitals in Denmark, i.e. Aarhus, Aalborg and Odense, can potentially be catalysers of a more rapid diffusion outside the eastern part of Denmark.

In the following, the diffusion of artificial intelligence and robotics is measured by the frequency of interaction between human workers and this type of technology. We have asked our respondents how frequent they interact with artificial intelligence and robotics in certain ways and whether this frequency has increased or not since 2016.[7] If the frequency has increased, we interpret it as an increased rate of diffusion of the technology in question. Regarding *robotics*, we ask about two types of interaction, i.e. how often the respondent (1) delivers inputs or receives output from a robot, and (2) start, monitor and stop a robot in order to accomplish a specific task. Regarding *artificial intelligence*, we ask about three types of interaction, i.e. how often the respondent (1) makes use of information compiled automatically by a computer or computerized machinery for making decisions or for advising clients or customers, (2) receives orders or directions generated automatically by such technology, and (3) use such technology that has the ability to automatically learn and improve from experience.

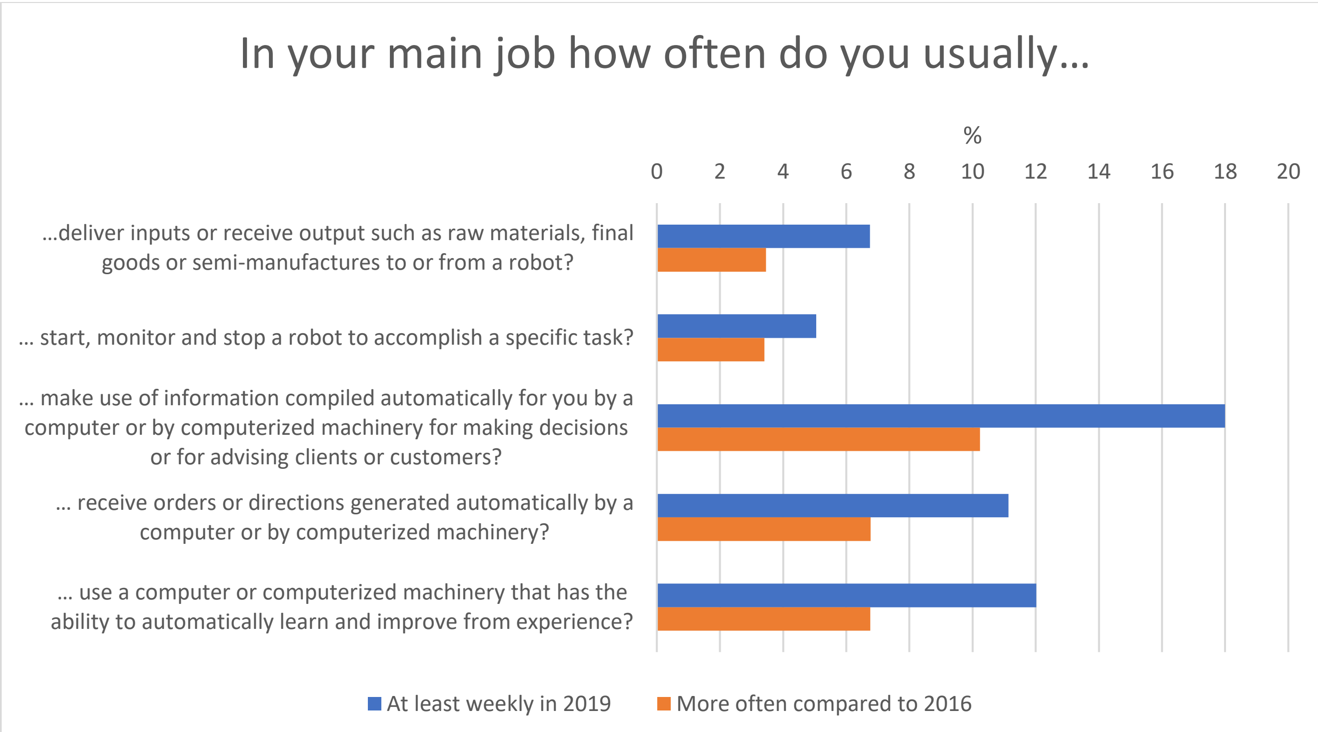
3.1. AI is more diffused than robotics and diffuses more rapidly

The public debate on human-technology interaction often yields the impression that robotics is a pervasive type of technology throughout the economy. However, as can be seen in figure 1, this is not the case in terms of the share of employees using the technologies. Furthermore, robotics cannot compare to artificial intelligence in this respect. Regarding robotics, 6.75 % of our respondents report that they deliver inputs or receive output from robots at least once a week, and 5.05 % tell that they start, monitor and stop a robot in order to accomplish a task at least once a week. These are rather small numbers of human-technology interaction when we compare with artificial intelligence. Almost one out of five respondents, i.e. 18.00 %, indicates that they make use of information compiled automatically by computers or computerized machinery for decision making, or for advising clients or costumers. Furthermore, when it comes to receiving orders from computers or computerized machinery, or to use technology that is able to learn and improve machinery, respectively 11.14 % and 12.02 % answer that this happens at least once a week. In addition, when compared to 2016, incidents of human-technology interaction in the case of artificial intel-

[7] See questions F1-F2 and G1-G3 in the appendix. The frequency is divided into “every day”, “at least once a week”, “1-3 times a month”, “less than a month”, and “never”. In section 3, we only report incidents that occur at least weekly, i.e. we have merged the first two categories.

ligence occurs much more. The wording of this question on the TASK survey entails that this increase includes both increases at the intensive and extensive margins – i.e. both increased use for existing users and the addition of new users.

Figure 1. AI is more diffused than robotics and diffuses more rapidly



Source: Appendix, F1-F2 and G1-G3

One might suspect that the more widespread and faster diffused use of artificial intelligence reflects the industrial composition of the economy, i.e. that a relatively high proportion of service industries would cause a more diffused utilization of artificial intelligence.[8] As can be seen from table 1, this is not the case, since the use of artificial intelligence is almost as frequent in manufacturing as in private service.

[8] While manufacturing and construction account for, respectively, about 12 % and 6 % of Danish employment, private service accounts for almost 45 %. If we include the public sector (31 %) and culture and leisure (5 %), the Danish economy proves to be highly service-driven. (Source: Calculations from Statistics Denmark, RAS300, https://www.statistikbanken.dk/10310).

Table 1. Diffusion of AI and robotics across main sectors

	At least weekly			
Questions	Manufacturing	Construction	Private services	Health and education
Input or outputs to/from robot	17.8	1.9	7.6	2.7
start, monitor and stop robot	17.3	0.0	4.0	2.8
AI information	25.7	4.7	23.8	11.5
AI directions	20.2	1.9	14.7	5.6
Automatically learning AI	15.9	5.2	13.1	11.3
	More often compared to 2016			
Input or outputs to/from robot	7.4	4.2	4.7	0.7
start, monitor and stop robot	9.3	0.0	3.1	2.2
AI information	14.3	0.0	14.2	6.5
AI directions	13.4	0.0	8.8	3.6
Automatically learning AI	8.3	3.6	8.5	5.3

Source: Figure 1 divided into main sectors

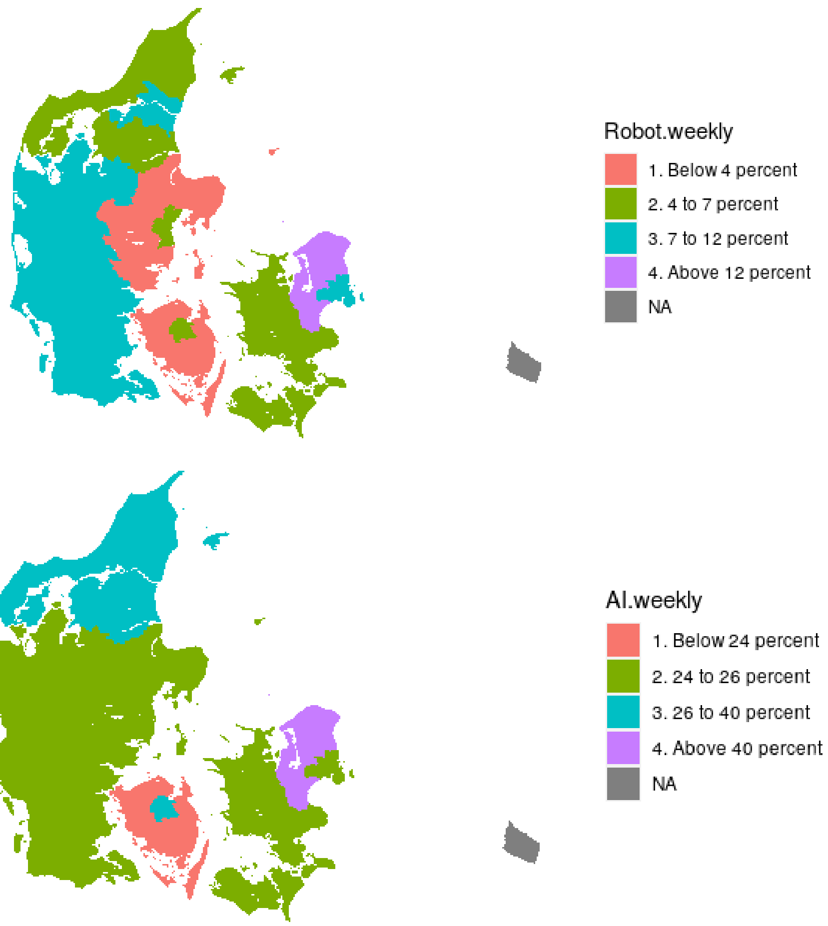
It is not surprising that advanced technologies, not least robots, are predominantly used in manufacturing, and that they are relatively infrequently used on construction, cf. table 1. The use of robots and artificial intelligence in health and education is less frequent compared to private services but it must be kept in mind that while people in some jobs may use new technologies very frequently, the sectors for health and education contain a wide variety of different jobs.

The discussion here focusses on the share of employees working with new technologies. In principle the share of output produced with a new technology or the share of the total capital stock consisting of a new technology may differ significantly from the share of employees working with the technology, if for example the technology is more diffused in the relatively capital intensive and high labour productivity manufacturing industries.

3.2. AI and robotics are more diffused in Eastern Denmark

The diffusion of artificial intelligence and robotics is to some extent unevenly distributed across regions in Denmark, as presented in figure 2. Robotics are more used in the eastern and northern parts of Zealand, while the use at Fyn outside the island's capital city Odense is quite low. Artificial intelligence is more used at the eastern parts of Zealand, while Fyn outside Odense once again distinguishes itself at the low end of the continuum. The main provincial capitals of Aarhus, Aalborg and Odense exhibit higher uses than the regions in which they serve as capital cities. The capital of Denmark, Copenhagen, deviates from the provincial cities in the sense that it tends to exhibit lower use than the region in which it is situated.

Figure 2. Uneven diffusion of AI and robotics across regions



Source: Figure 1 divided into NUTS3 regions with Aalborg, Odense and Aarhus indicated separately

Bornholm (NUTS3: 1D) has been excluded because of too few observations.
The city of Copenhagen and the Copenhagen region (NUTS3: 1A and 1B) are merged.

The high diffusion of both artificial intelligence and robotics in East and North Zealand probably reflects that a lot of relatively large manufacturing plants in knowledge intensive industries such as pharmaceuticals are located in the regions. Outside of the main cities it can be seen that robotics are relatively more diffused in West and South Jutland, while artificial intelligence is relatively more diffused in North Jutland. This probably reflect that Jutland is home to a large share of Danish manufacturing, and the relatively lower diffusion in East Jutland can reflect a somewhat diversified industry structure in that region where the manufacturing sector may be large in absolute terms but is complemented by a large range of activities in other sectors.

We may conclude from this that there is a need for diffusing artificial intelligence and robotics outside the eastern and northern parts of Zealand, and that regional capitals could serve as catalysers to that effect.

4. Effects on skills

In this section we show that Danish employees are very confident in using artificial intelligence and robotics, because they feel that they have the necessary skills for doing so. This is especially the case when using robots for accomplishing a specific task, and when interaction with artificial intelligence is focused on using information and receiving orders or directions that are automatically generated. Training by peers at work is extremely important in order for employees to have the skills necessary to use artificial intelligence and robotics. However, artificial intelligence requires a broader range of learning arenas, and learning by doing and formal training are more important when using artificial intelligence than when using robotics.

In the following, we look further into the sentiments among those respondents that are frequent users of artificial intelligence and robotics, i.e. the proportion of respondents that indicates that they use artificial intelligence and robotics at least weekly. We show the extent to which they feel that they have the skills necessary for undertaking the kind of human-technology interaction that were explored in the previous sections, and the way in which they have acquired these skills. This exploration reflects our previous reflections in section 2 that the implementation of artificial intelligence and robotics is sensitive to upskilling and development of new competencies, and how employees embrace and accommodate to these opportunities.

4.1. Employees are very confident in using AI and robotics

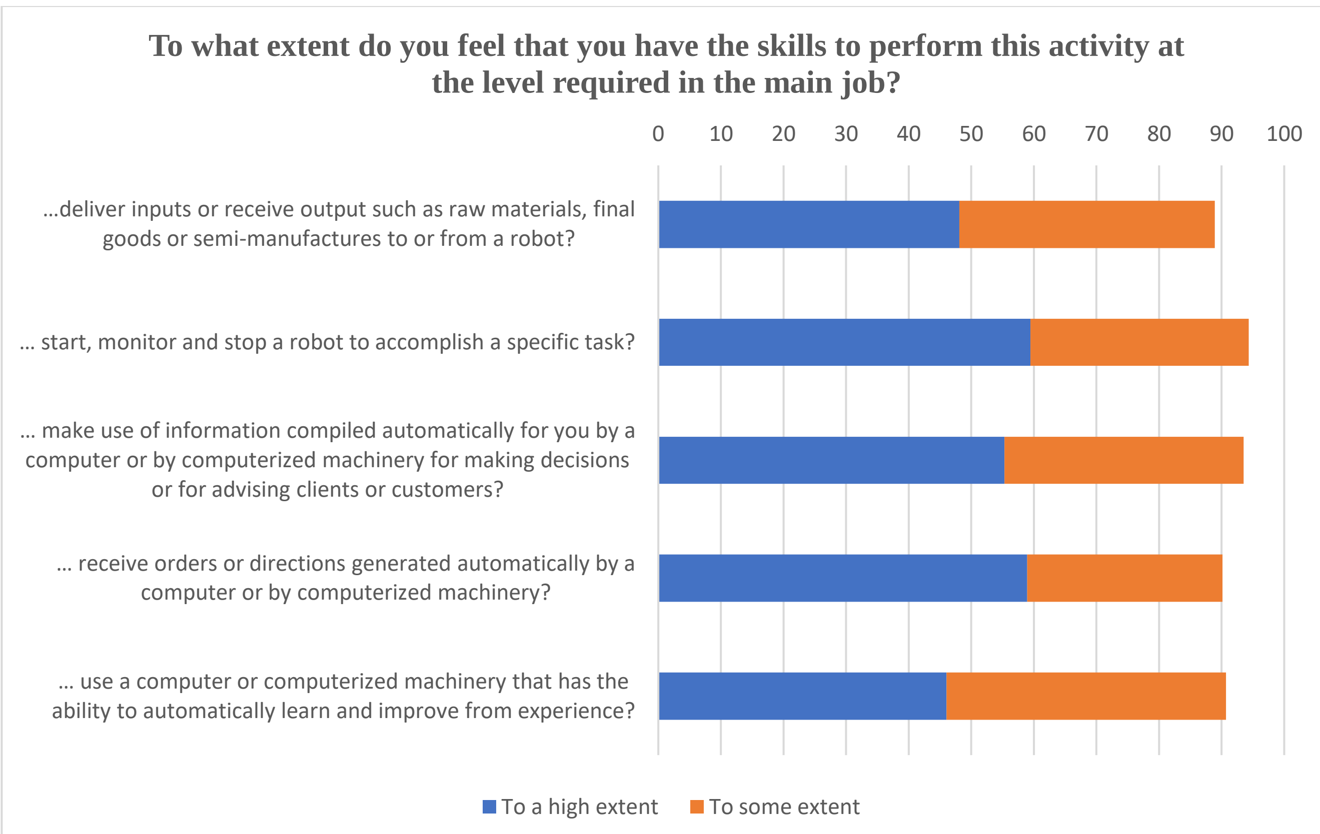
Figure 3 displays how the frequent users of artificial intelligence and robotics feel about their skills in relation to artificial intelligence and robotics. In general, nine out of ten respondents feel that they have the necessary skills to operate artificial intelligence and robots. This is a high level of individual efficacy[9] especially in the cases of operating a robot, make use of information, and receive orders and directions, where the proportion of respondents answering "to a high extent" is significantly larger than the proportion of respondents indicating "to some extent".

The high level of self-efficacy in the case of artificial intelligence and robotics may reflect a high level of self-efficacy in general. Overall, a huge proportion of our respondents report that they are "very satisfied" (42,2 %) or "satisfied" (46,3 %) with working conditions in their current main paid job (appendix, D1). Furthermore, we have also taken the opportunity to ask our respondents about the kind and frequency of social interaction in their job in general (appendix, section E). Social interaction is defined in terms of four types of activities, i.e. that the employee (1) advice, instruct, train or teach people individually or in groups, (2) sell a product or sell a service, (3) negotiate contracts or terms more generally with people inside or

[9] Individual efficacy, also known as perceived self-efficacy, is understood as "people's domain-specific perceptions of their ability to perform the actions necessary to achieve desired outcomes", cf. Gallagher (2012). The concept, which is a core concept in organization psychology studies on work organization, was originally proposed in Bandura (1977). Self-efficacy is an important determinant for the effort and persistence by which employees pursue new and unfamiliar tasks, set goals for themselves, and engage in learning, e.g. Bandura (1997).

outside the firm, or (4) share work related information with people inside or outside the firm. Frequent social interaction occurs mainly in the case of (1) advice, instruct, train or teach and (4) share work related information, where, respectively, 46.2 % and 56.9 % of the respondents report that this kind of social interaction occurs at least weekly (appendix, E1-E4). In all four cases, frequent social interaction is characterised by the fact more than nine out of ten respondents feel that they have the skills necessary for performing these activities to a high or some extent (appendix, E1C-E4C).

Figure 3. Employees feel confident in using AI and robotics



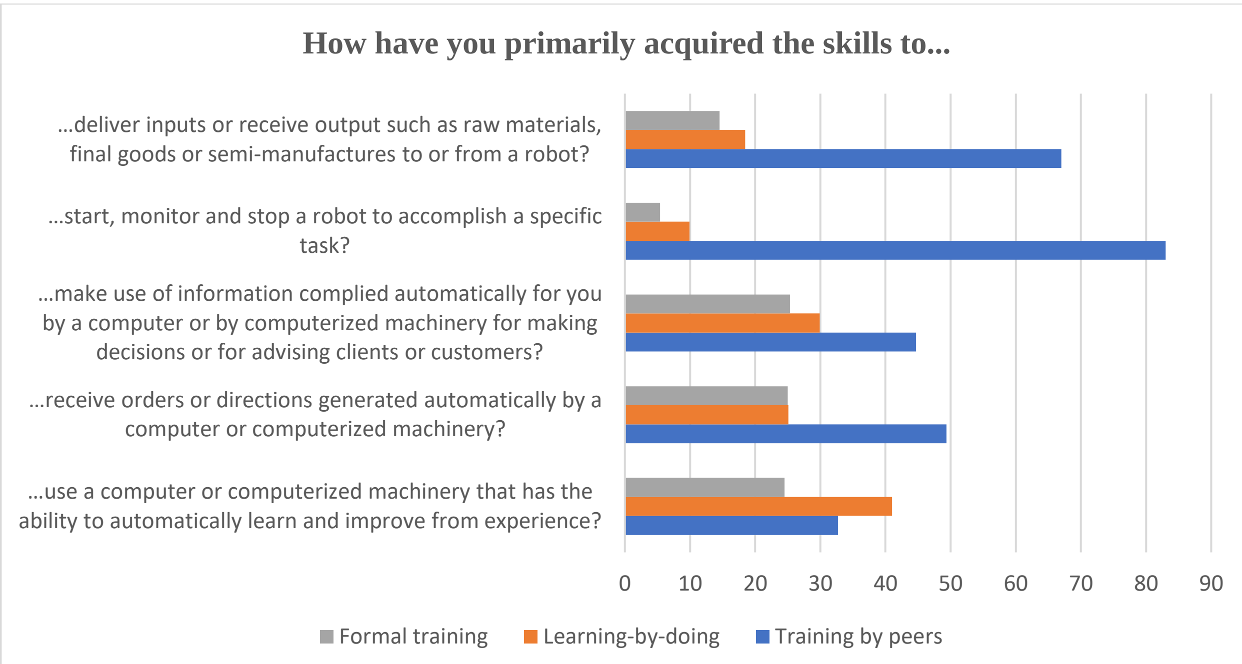
Source: Appendix, F1C-F2C and G1C-G3C

4.2. AI requires more learning arenas than robotics

Self-efficacy in performing a task depends on the employee's experience with the results of performing that task, which is both a result of the frequency by which the task is undertaken, and the knowledge that accumulates while performing the task more than once. So, when performing a task occurs more frequent, and when learning occurs during task execution, self-efficacy increases.

While figure 1 reveals that performing the tasks in question related to artificial intelligence and robotics has increased during 2016-2019, figure 4 shows the kind of learning that has been associated with using artificial intelligence and robotics during that period of time.

Figure 4. Training by peers and learning by doing are more important than formal training



Source: Appendix, F1B-F2B and G1B-G3B

Learning is conceived in three forms, i.e. (1) formal training such as classroom and online courses, (2) training by peers at work such as experienced colleagues and supervisors, and (3) the employee's own learning by doing, possibly using teaching materials such as books and videos etc. Training by peers is by far the predominant kind of learning when it comes to robotics and is also quite dominant in the case of artificial intelligence. However, learning by doing and formal training appears to be more important when using artificial intelligence than when using robotics. In sum, it appears that artificial intelligence requires a broader range of learning arenas than robotics.

5. Effects on work organization

In general, jobs in Denmark tend to be complex, empowering, and requiring self-reliance on behalf of the employees. While artificial intelligence and robotics imply a potential for dehumanization as well as empowerment and inclusion, the task environment in Danish firms favour the latter rather than the former. As argued in section 2, the actual effects of implementing artificial intelligence and robotics depends on the socio-technical system and thus how humans and technology co-exist. Our survey shows that artificial intelligence has more applications than robotics, and that artificial intelligence to a higher extent than robotics is relevant to complex social interaction, problem-solving, and decision making. This is especially the case for managers and white collar, and for high and medium skilled employees.

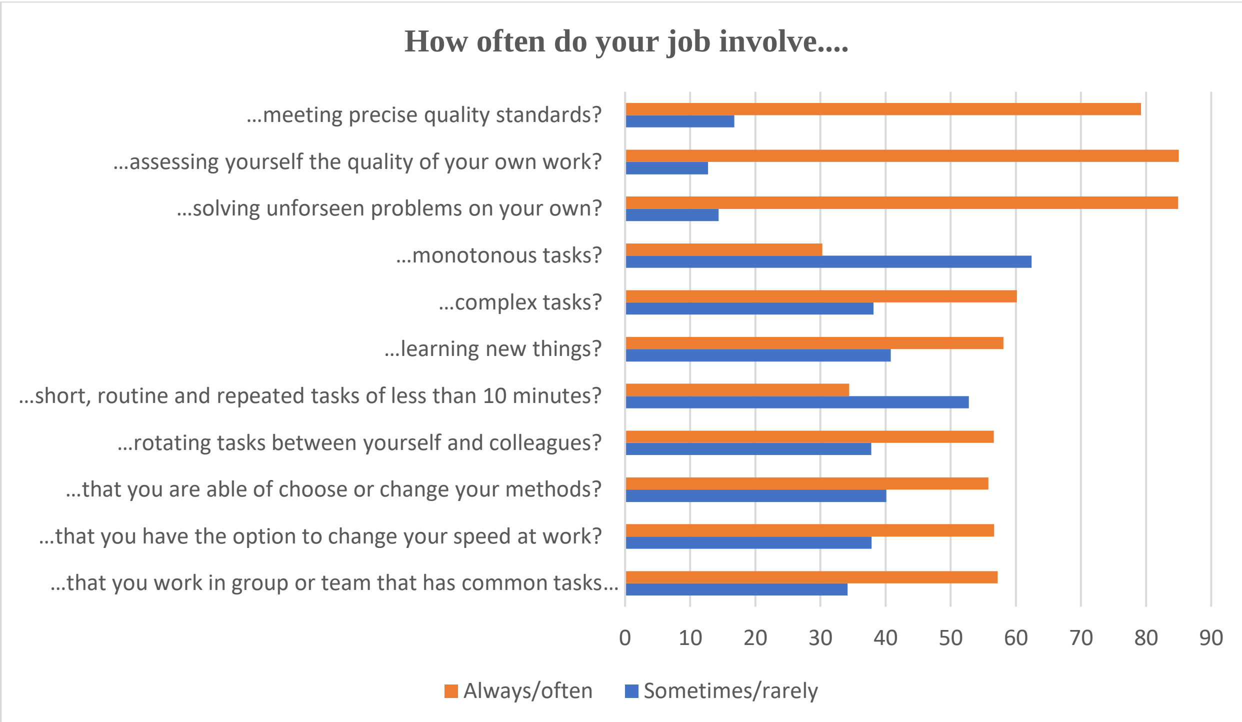
In the following, we describe the work organization that characterises our sample, and explore the relationship between types of job content and human-technology interaction. Types of job content appear in three dimensions, i.e. (1) various tasks that our respondents' jobs involve (appendix, B1-B11), (2) various sources of the pace of work (appendix, B12-B15), and (3) various forms of social interaction incurred in the job (appendix, E1-E4). The human-technology interaction is represented by the form of interactions that were explored in figure 1 and onwards. Finally, we show the use of artificial intelligence by types of occupation and skills (appendix, A2). Regarding occupation, we distinguish between management, white collar, and blue collar, while skills are divided into high, medium, and low.[10]

5.1. Jobs are complex, empowering, and require self-reliance

Figure 5 reports on various aspects of job content, ranging from monotonous and repetitive tasks to tasks that requires high levels of individual judgement and decision making. It appears that meeting precise quality standards, assessing the quality of their own work, and solving unforeseen problems on their own are job contents that are always or often experienced by our respondents. In contrast, monotonous tasks, and short, routine and repeated tasks are more likely to be experienced only sometimes or rarely. The remaining types of job content, which have to do with teamwork and opportunities for influencing the speed and execution of work, are always or often experienced by more than half of the respondents. In sum, these observations indicate that Danish workplaces are predominantly characterised by a relatively high level of complexity requiring empowerment and inclusion, when it comes to the actual execution of job content.

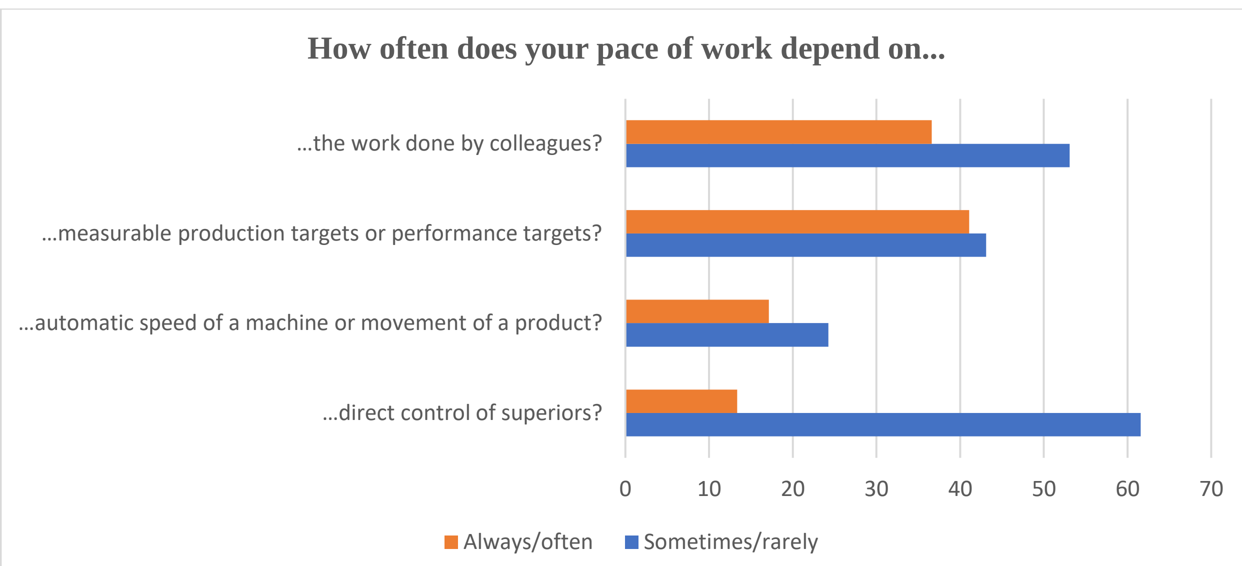
[10] We use nine of the ten job titles in A2 in order to construct these types, omitting armed forces occupation because of zero respondents. The job titles are. (1) Managers, (2) professionals, (3) technicians and associated professionals, (4) clerical support workers, (5) service and sales workers, (6) skilled agricultural, forestry and fishery workers, (7) craft and related workers, (8) plant and machine operators, and assemblers, and (9) elementary occupations. Management is defined as job title (1), white collar as job titles (2)-(5), and blue collar as job titles (6)-(9). High skill is defined in terms of job titles (1)-(3), medium skill in terms of job titles (4) and (7)-(8), and finally low skill in terms of job titles (5) and (9). See also figure 8.

Figure 5. Jobs are complex, empowering, and require self-reliance



Source: Appendix, B1-B11.

Figure 6. The pace of work is mainly regulated by targets and colleagues



Source: Appendix, B12-B15

When the execution of job content takes place within a context that is complex, empowering, and require self-reliance on behalf of the employee, we might expect that the pace of work is less regulated by control exerted by supervisors or technology and, vice versa, more regulated by interaction with colleagues and targets that need to be met. As figure 6 shows, this is actually the case. Less than one out of five respondents report that their pace of work depends on direct control of supervisors or the automatic speed of equipment or machinery , while more than one out of three tell that the pace of work is always or often regulated by targets or work done by colleagues.

5.2. AI has a broader impact on job content that robotics

Our previous observation that artificial intelligence involves more learning arenas than robotics may reflect that artificial intelligence to a larger extent is applicable to more organizational activities than robotics. While robotics primarily pertain to the physical aspects of organizational life in terms of processing and handling physical objects, artificial intelligence is relevant to both physical and non-physical aspects of organizational life. Artificial intelligence enters the planning, execution and controlling of physical processes as well as the planning, execution and controlling of services, problem finding, problem solution, and decision making. In effect, artificial intelligence serves more purposes than robotics.

In consequence, it can be expected that artificial intelligence has a broader impact on job content than robotics. To some extent, our survey points in that direction, cf. figure 7 that reports our findings on the association between the different types of job content that have been discussed so far and the different types of human-technology interaction that is reported in figure 1 and onwards. Three important observations appear in figure 7. First, artificial intelligence is positively correlated with far more types of job content than robotics. Second, robotics are mostly associated with types of job content that concerns execution and controlling of work, while artificial intelligence is also associated with types of job content that reflect complex social interaction. Third, solving unforeseen problems through human-technology interaction only occurs in the case of artificial intelligence and not in the case of robotics. These observations indicate that artificial intelligence to a larger extent than robotics is instrumental in supporting managerial intentions that work against dehumanisation of work and favours empowerment and inclusion. Or, it could be argued that in order to get the most out of using artificial intelligence, managerial intentions must focus on how to create work organizations that allow for human creativity, problem solving, and decision making.

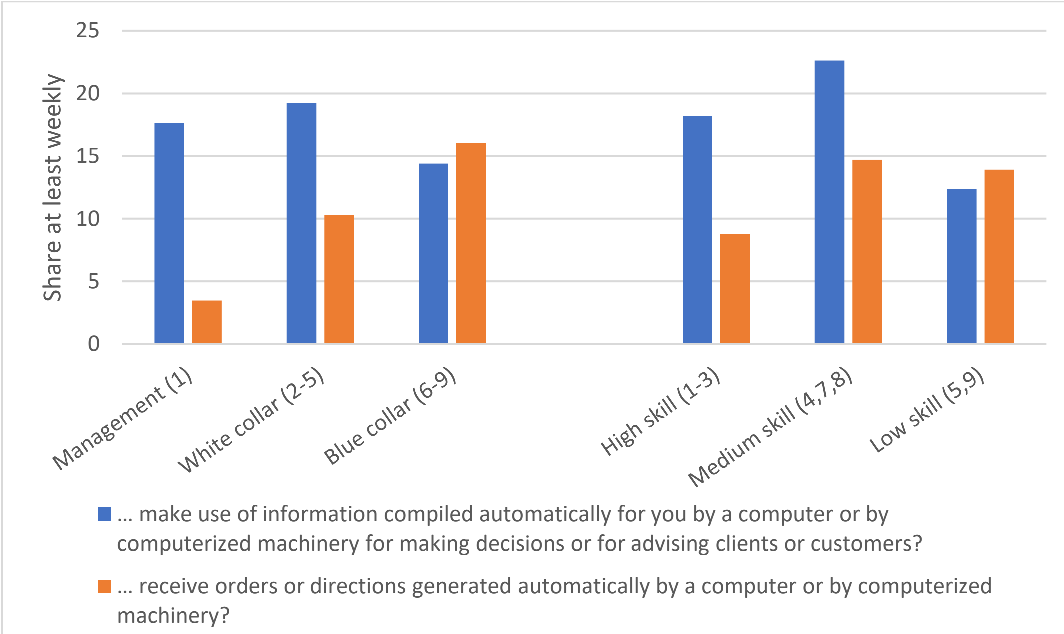
While artificial intelligence has a broader impact on job content than robotics, there is, nevertheless, a marked difference in human-technology interaction across occupational lines and levels of skills, cf. figure 8.

Figure 7. Artificial intelligence has a broader impact on job content than robotics

F1-F2, G1-G3 / B1-B15 E1-E4	Deliver inputs or receive outputs to/from robots	Start, monitor, and stop a robot	Use automatic information for decisions or advise	Receive orders or directions automatically generated	Use technology that learns and improve automatically
Meeting quality standards	***	***	***	***	***
Assessing quality of own work					
Solving unforeseen problems			***		
Monotonous tasks					
Complex tasks			**		
Learning new things	**		***		***
Short, routine, repeated tasks		**		**	
Rotating tasks			**		
Choose or change methods					
Option to change speed of work					
Teamwork	**	**	**		
Work done by colleagues		***			**
Measurable Targets	***	***	***	***	***
Automatic speed	***	***	***	***	***
Direct control	**	**	***	***	***
Advice, instruct, or train	***		***		***
Sell a product or service			**	**	**
Negotiate contracts or terms			***	***	**
Share work related information			***	***	***

The left column contains the different types of job content that appears in questions B1-B15 and E1-E4 in the appendix, while the top row contains the types of human-technology interaction that were presented in figure 3 and appears in questions F1-F2 and G1-G3 in the appendix. Regarding B1-B15, respondents answering "always" or "often" are included. Regarding E1-E4, F1-F2 and G1-G3, respondents that indicate at least weekly are included. The number of * indicate the strength of a positive correlation ** indicates significant at 5 % while *** indicates significant at 1 %. No negative correlations were found.

Figure 8. AI use reflects the organizational hierarchy



Source: See footnote 16.

The respondents are those who indicate that they use artificial intelligence at least once a week, i.e. the same group of respondents who enter figure 1.

Figure 8 shows that the use of artificial intelligence for, respectively, decision making and receiving directions varies with organizational hierarchy and skill levels. While the use of artificial intelligence for decision making is predominant in the case of management and white collar employees as compared to the use of artificial intelligence for receiving directions, this is less so the case for blue collar employees, where the use of artificial intelligence is evenly spread across decision making and receiving directions. This reflects, of course, that we are observing different types of organizational roles where decision making is more relevant at higher levels of the organizational hierarchy, while directions are more relevant at lower hierarchical levels. In the case of skills, high and medium skilled employees show similar patterns, where artificial intelligence for decision making is used more often than for receiving directions. However, both types of use are more frequently observed among medium skill workers. Low skilled employees have an even distribution across the two types of use. This may reflect that decision making is a more important part of job execution in high and medium skilled occupations than in low skilled occupations.

6. Needs for skills formation

This section shows that there is a need for focussing on future skills formation. In the present situation, the use of artificial intelligence and robotics is associated with a high level of self-efficacy, as previously discussed in section 4.1 which showed that Danish employees are very confident in using artificial intelligence and robotics, and nine out of ten find that they have the necessary skills for the types of human-technology interaction that we have explored in this working paper. However, there is a need for focussing on future skills formation, because the demands on skills formation is bound to increase, as the use of artificial intelligence and robotics diffuses further and becomes more advanced.

In the following, we look further into the need for future skills requirement among those respondents that are users of artificial intelligence and robotics. The discussion is a mirror of the previous discussion in sections 4.1-4.2, where we showed the extent to which our respondents feel that they have the necessary skills to a high or some extent (figure 3), and the source of how these skills were acquired (figure 4). In this section we focus on the respondents that do not feel that they have the necessary skills to a high extent.

6.1. Half of Danish employees lack skills for future use of AI and robotics

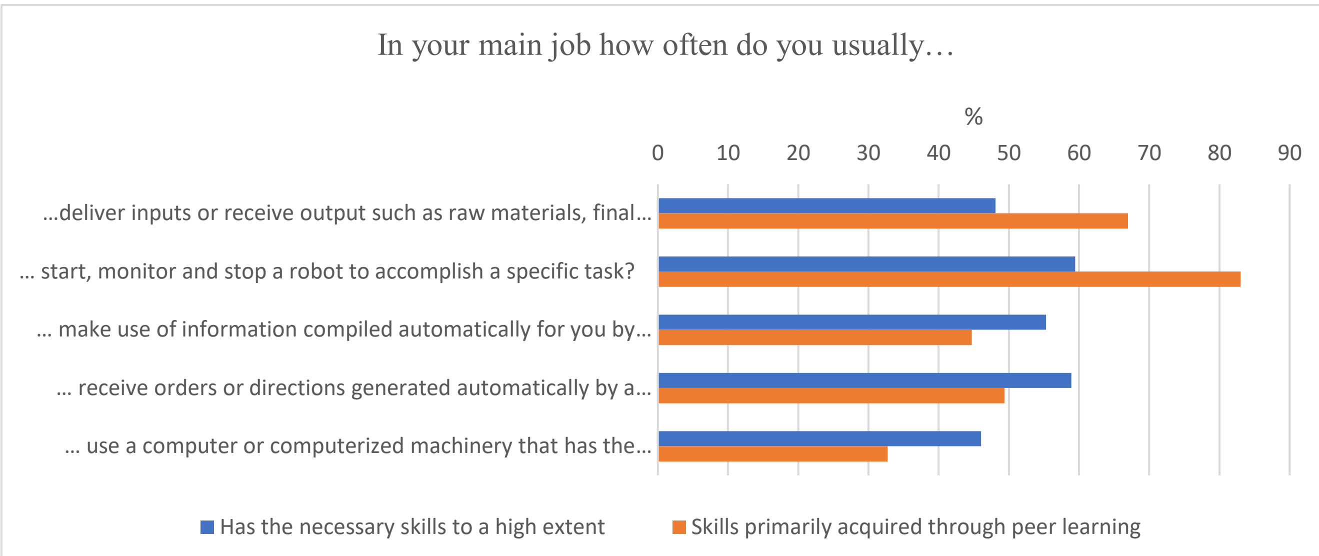
The primary labour market effect of using artificial intelligence and robotics is that the future proliferation of new types of jobs will be accompanied by the disappearance of current types of jobs. Even if the net effect of these changes is that the number of job increases, there is no guarantee that current employees will benefit from the changes, unless their qualifications keep up with the skills requirement entailed in the new types of jobs. As explained in section 2, the common denominator for the new types of jobs is the high-skilled ability to create, engage, interpret, judge, and act upon data and activities involving artificial intelligence and robotics (World Economic Forum, 2020a). The World Economic Forum (World Economic Forum 2020b) argues that the change of the composition of tasks is to some extent driven by transformation of value chains in which deep technological integration plays an important role, consequently pushing the frontier in the human-technology interaction in a way that gradually renders a number of current traditional job roles obsolete.[11] Obsolescence of jobs is related to information handling and data processing, technical/physical/manual work activities, communication and interaction, reasoning and decision making, and activities concerning coordination, management, advising and development. In consequence, skills gaps are expected to occur in these task areas, unless upskilling of human capital takes place.

This means that employees who find that they do not or only to some extent have the skills necessary for the required human-technology interaction may be challenged in terms of future needs for upskilling of

[11] The traditional job roles mentioned in the World Economic Forum (2020b) fig. 22, p. 30 are: Data entry clerks; administrative and executive secretaries; accounting, bookkeeping and payroll clerks; accountants and auditors; assembly and factory workers; business services and administration managers; client information and customer service workers; general and operation managers; mechanics and machinery repairers; material-recording and stock-keeping clerks; financial analysts; postal service clerks; sales representatives; relationship managers; bank tellers and related clerks; door-to-door sales, news and street vendors; electronics and telecom installers and repairers; training and development specialists; and construction laborers.

human capital. As shown in figure 9, the proportion of respondents who find that they to a high extent has the necessary skills for the human-technology interactions in question is in the range of 40-60 %, which indicates that about half of the respondents are, to some extent, challenged by future needs for upskilling.

Figure 9.Only half of the respondents feel that they have the necessary skills to a high extent, and these skills have primarily been acquired through peer learning



Source: Appendix, F1C-F2C, G1C-G3C, F1B-F2B and G1B-G3B

The main source of upskilling is peer learning, i.e. "Training by peers at work such as experienced colleagues and supervisors". This is especially the case when it comes to robotics, where 70-80 % of the respondents report this kind of learning as their main source of upskilling. In the case of artificial intelligence, peer learning is reported by less than 50 % of the respondents, reflecting that artificial intelligence requires a broader range of learning arenas than robotics, as previously argued in section 4.2.

The dominant role of peer learning as an avenue for upskilling may, in the long run, not be sufficient for developing and sustaining the level of upskilling that is necessary for adopting robotics and artificial intelligence. The new types of job roles that are gradually appearing will require more formalized training and education, not only in technical and hard skills, but also in soft skills like team, analytical thinking, multitasking, and documentation skills.[12] While skills for the new job types can be refined in practice through

[12] An interesting analysis of skill gap in robotics is found in Shmatko & Volkova. (2020. Data mining open access vacancies and conducting a number of expert interviews, they compare requirements for robotics professionals, i.e. engineers and researchers, in USA and Russia. Pointing to a general shortage of this kind of labour, they argue in favour of lifelong learning and education. As robotics become more diffused throughout the economy, we might expect that the skill gap identified for professionals might reflect a more general skill gap throughout the workforce.

peer learning, they still need a formalized and systematic education and training framework in order to be acquired, implying sequential or simultaneous use of a range of learning arenas. Since the rate of technological change in the fields of artificial intelligence and robotics seems to increase, there might be a tendency to either reduce the human side of the human-technology interaction or increase the quality of human input to the interaction, which might imply that middle-range skilled jobs are the ones most likely to be destroyed by robotics and artificial intelligence, while low-skilled and high-skilled jobs may proliferate.[13] In effect, firms and society must focus on how to upskill middle-range positions in order to create more professionals, which implies that formal training and education becomes important prerequisites for learning while working.[14]

In sum, there is a need for society and firms to focus on upskilling for using artificial intelligence and robotics. This need arises from the fact that only half of the respondents feel that they have the skills necessary for the types of human-technology interaction that we have analysed in this working paper. As technological change progresses at an increasing rate, these respondents risk being left behind or degraded to human assistants for hard- and software operations. In the long run, this may hamper the development of the knowledge base of private and public firms, and the society's ability to take part in the economic growth created by the new types of jobs and activities entailed in the diffusion of artificial intelligence and robotics.

[13] This possibility is pointed out by many researchers and observers in the field, cf. Makridakis (2017).

[14] In their large scale survey on the determinants of 21st-century digital skills, Ester van Laar and colleagues find that formal training to some extent eliminates the need for help from colleagues at the workplace, and that help from colleagues primarily contributes to the development of collaboration and problem-solving skills, see van Laar et al. (2019). This might indicate that the most important contribution from peer learning is the refinement and sustained development of skills acquired through formal training and education. In general, however, research is still needed in order to determine the synergy from combining different types of learning arenas, and in order to understand which determinants are important for which types of skills, cf. van Laar et al. (2017; 2020).

7. Recommendations for policy and management

The present working paper has shown that artificial intelligence and robotics imply changes of work organization and skills, because it creates new varieties of socio-technical systems. Of course, we have known for many years that technology poses demands on the type of organizational structure that is needed for the effective use of the technology in question, and following upon the seminal work by Joan Woodward on the interplay between management, technology and industrial organization (Woodward, 1958; 1965; 1970) the idea of a technological imperative even enjoyed prominence for years to come.[15] During her studies of multiple cases in post war industrial Britain, Woodward, among other things, showed that empowerment and employee discretion were more prominent in cases of unit or process production than in cases of mass production where line-staff organization and top-down decision making prevailed. However, in order to make such clear delineations, we need to be able to define technology uniformly and assume a direct link between technology and organizational structure. This is far from trivial since we find different technologies with different uses within the organization, where the application of technology is influenced by the nature of tasks that technology helps to solve, and by the principles of control and coordination that are applied. The present study has focused on types of technology-human interaction and what we can learn from these types, and what we have learned can be grouped into two broad categories of observations, which are issues regarding *diffusion* and issues regarding *skills and opportunities*.

7.1. Issues regarding diffusion

We observed that artificial intelligence seems to be more diffused than robotics, and that it apparently diffuses more rapidly. This tendency was prevalent in both manufacturing and service. What this implies for both policy and management is that there is a need to be more focused on the benefits and challenges that artificial intelligence entails for technology-human interaction and managerial discretion. In particular, our findings indicate that artificial intelligence has a broader impact on job content than robotics, which means that the organizational set-up and the composition of task environments within firms and organizations are more sensitive to the application of artificial intelligence than robotics. So, as artificial intelligence continues to diffuse, we might expect an increasing variety of sociotechnical systems. This is a potential source of competitive advantage by which firms can differentiate themselves in terms of how they develop and exploit dynamic capabilities, and how processes are being optimized. In order to reap the benefits accruing from this development, management must focus on how to develop and sustain human capital. As argued in section 2, a large variety of new types of jobs are likely to appear, which effects how sociotechnical systems are planned and evolve, and in order to develop and sustain the human capital warranted by this development management must strategically plan for continuous learning. The concomitant

[15] See e.g. "The South Essex experience" (pp. 11-15) in Gjerding (1996. It is fair to say, of course, that the idea of a technological imperative or something similar to that effect can be traced back to times long before Joan Woodward, e.g. Henry Ford's studies on work organization in Ford (1911) and Karl Marx's studies on value chains and division of labour within different types of manufacturing in the first volume of Marx (1867), notably chapter 12.

implications for policy making is that new types of vocational and academic education and training need to be developed and implemented, including improved conditions for lifelong learning.

It appeared from our findings that artificial intelligence and robotics are more diffused in Eastern Denmark as compared to other parts of the country, and that larger Danish cities serving as regional capital cities are more extensive users of artificial intelligence and robotics than the regions to which they belong. This might call for policy schemes for technological diffusion to be more focused on targeting peripheral areas.

Our analysis has focused on human-technology interaction as an endogenous phenomenon within firms. In doing so, we have not contemplated the implications of regarding human-technology interaction as a phenomenon that spans organizational borders. However, this type of technological fit is widely disputed in terms of the creation of a precariat that is characterized by freelancing and short term contractual employment (Standing, 2011). The precariat is associated with what Sarah Kessler calls the *gig economy* where permanent employment and full-time jobs disappear in favour of various types of temporary, part-time or contract-based jobs (Kessler, 2018). This kind of fragmentation of sociotechnical systems may benefit people who are up to speed with recent technological trends and high-skilled job requirements, but also create an impoverished labour force. This calls for more elaborate policy schemes for training and re-education as well as new vocational and academic educations that empower people to take part in ongoing and upcoming technological and social trends.[16]

7.2. Issues regarding skills and opportunities

The preceding analysis also addressed the need for skills for the future in terms of our finding that even though employees are very confident in using artificial intelligence and robotics, many employees lack the skills for future use of these technologies. Peer learning appeared to be a dominant form of upskilling, especially in the case of robotics, while artificial intelligence required a broader range of learning arenas. However, the new types of jobs that gradually appear call for more formalized training and education in both hard and soft skills. Peer learning will still be important as an avenue to knowledge exchange and the development of practice at work, but the effect of peer learning will be increasingly contingent on the extent and quality of formalized training and education. Middle-range skilled jobs are likely to be destroyed to a larger extent than other job types, so firms and society must focus on how to create more professionals by upskilling middle-range positions. As argued in the preceding section, creating opportunities for acquiring new skills and occupying new types of jobs is a lifelong achievement.

Our findings point to a need for not only developing new types of educations and upgrading existing ones, but also for a stronger focus on how formal training and education interact with practice-based learning at work. While formal training and education may be a prerequisite for learning at work, learning at work

[16] The COVID-19 situation may speed up the creation of a precariat. In a recent analysis of 2,000 tasks in 800 jobs and 9 countries, McKinsey finds that the proliferation of hybrid models of remote work that has occurred during the COVID-19 lockdowns is likely to persist after the end of the pandemic. We might hypothesize that there is but a small leap from hybrid models of remote work to gig economy conditions. The analysis in question is Lund et al. (2020).

can also serve as an important arena for translating formal training and education into practice. Reaping the benefits from formal training and education combined with learning at work requires that management must create favourable conditions for developing and sustaining human capital. This calls for structural and processual arrangements that enable learning organizations[17], where technology-human interaction enjoys opportunities for continuous adjustment.[18]

In sum, the diffusion of artificial intelligence and robotics requires policy makers and the educational system to rethink current educations and develop new ones. How formal education and training can be exercised through learning on the job and how learning on the job can benefit from formal education and training must be an integral part of how current educations are renewed and new educations are developed. How sustained development of human capital within firms can benefit from these changes is an important managerial task that probably calls for an upgrading of strategic human resource management.

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[17] Learning organizations can take many forms. Peter Senge described the learning organizations in terms of the exercise of five disciplines: Systems thinking, personal mastery, mental models, building shared vision, and team learning, cf. Senge (1990). Karl Wiig focused on structures and procedures for knowledge management in Wiig, (1993). Nonaka and Takeuchi described the learning organization in terms of how knowledge is externalized and internalized through processes of socialization and combination of elements of knowledge in Nonaka & Takeuchi (1995. In a recent interview, Silvia Gherardi argues that in contemporary research the idea of a learning organization often appears in the disguise of dynamic capabilities, knowledge management or change management, see Cuel, (2020).

[18] In a recent contribution, Salima Benhamou shows how forms of work organization that stimulates learning contributes to complementarity between technology and humans in the health, transport and banking sectors, see Benhamou (2020).

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Appendix 1 Full tables

This appendix reports the data from the TASK survey.

The occupations in questions A2 and A5_1 are manually coded by experts at Statistics Denmark based on two questions each. The first question is "What is the job title of your job" and the second is "what type of job do you perform most of the time in your job". The experts created 4-digit ISCO codes but they are here reported as 2-digit codes.[19]

Questions A3 and J1 pertain to municipalities but here the data are aggregated to the regional (NUTS3) level.

A. Introduction

This survey concerns the use of technology in Danish jobs.

	Yes	No	Refuse	Don't know
A1. Do you currently have a main paid job?	87.87	11.54	0.12	0.47

Weighted pct. Unweighted N=1244.

	Yes	No
A1a. Have you ever had a main paid job?	63.03	36.97

Weighted pct. Unweighted N=115. Filter: A1=" No".

A2. What is the job title of your main job?	
0 Armed Forces Occupations	
03 Armed forces occupations, other ranks	0.08
1 Managers	
11 Chief executives, senior officials and legislators	1.57
12 Administrative and commercial managers	2.12
13 Production and specialised services managers	1.82
14 Hospitality, retail and other services managers	0.05

[19] The original dataset has an error where some of these manually coded ISCO classes only have 3 digits. Thus, any users of the dataset need to make sure that a trailing zero is added so that, for example, 234 becomes 2340.

2 Professionals	
21 Science and engineering professionals	1.99
22 Health professionals	5.94
23 Teaching professionals	15.21
24 Business and administration professionals	5.33
25 Information and communications technology	3.96
26 Legal, social and cultural professionals	1.76
3 Technicians And Associate Professionals	
31 Science and engineering associate professionals	4.38
32 Health associate professionals	2.10
33 Business and administration associate professional	8.40
34 Legal, social, cultural and related associate professionals	1.45
35 Information and communications technicians	0.57
4 Clerical Support Workers	
41 General and keyboard clerks	6.11
42 Customer services clerks	0.96
43 Numerical and material recording clerks	3.47
44 Other clerical support workers	0.38
5 Service And Sales Workers	
51 Personal service workers	1.85
52 Sales workers	2.67
53 Personal care workers	6.17
54 Protective services workers	0.51
6 Skilled Agricultural, Forestry and Fishery Workers	
61 Market-oriented skilled agricultural workers	0.19
62 Market-oriented skilled forestry, fishery and hunt	0.20
7 Craft and Related Trades Workers	
71 Building and related trades workers, excluding electricians	2.71
72 Metal, machinery and related trades workers	1.96

73 Handicraft and printing workers	0.16
74 Electrical and electronic trades workers	1.31
75 Food processing, wood working, garment and other	0.52
8 Plant and Machine Operators, And Assemblers	
81 Stationary plant and machine operators	2.09
82 Assemblers	0.26
83 Drivers and mobile plant operators	4.44
9 Elementary Occupations	
91 Cleaners and helpers	2.50
92 Agricultural, forestry and fishery labourers	0.26
93 Labourers in mining, construction, manufacturing	2.47
94 Food preparation assistants	1.42
96 Refuse workers and other elementary workers	0.62

Weighted pct. Unweighted N=1048. Filter: A1=" Yes". Missing: 73.

A3. In which municipality is the address of your main job?	
Copenhagen	14.88
Copenhagen Environs	13.69
North Zealand	4.99
Bornholm	0.81
East Zealand	2.97
West and South Zealand	8.09
Funen	7.83
South Jutland	13.40
East Jutland	17.18
West Jutland	6.22
North Jutland	9.94

Weighted pct. Unweighted N= 1121. Filter: A1=" Yes".

A4. In your own opinion what was the main reason you lost your previous job? (if yes in A1a)	
Work pressure was too high	7.68
I was offered a better job	5.02
My job was outsourced to another country	2.60
Other reason	84.13
Don't know	0.56

Weighted pct. Unweighted N=77. Filter: A1a=" Yes".

	Yes	No	Refuse	Don't know
A5. Did you have a main paid job in 2016?	90.08	9.76	-	0.16

Weighted pct. Unweighted N= 1121. Filter: A1=" Yes".

A5_1. What was the job title of your main job in 2016?	
0 Armed Forces Occupations	
Armed forces occupations, other ranks	0.00
1 Managers	
11 Chief executives, senior officials and legislators	1.70
12 Administrative and commercial managers	2.54
13 Production and specialised services managers	2.20
14 Hospitality, retail and other services managers	0.13
2 Professionals	
21 Science and engineering professionals	2.13
22 Health professionals	6.54
23 Teaching professionals	13.76
24 Business and administration professionals	6.37
25 Information and communications technology	4.34

26 Legal, social and cultural professionals	1.90
3 Technicians And Associate Professionals	
31 Science and engineering associate professionals	4.24
32 Stationary plant and machine operators	2.61
33 Health associate professionals	8.32
34 Business and administration associate professional	1.22
35 Information and communications technicians	0.45
4 Clerical Support Workers	
41 General and keyboard clerks	5.12
42 Customer services clerks	0.82
43 Numerical and material recording clerks	2.73
44 Other clerical support workers	0.70
5 Service And Sales Workers	
51 Personal service workers	2.09
52 Sales workers	2.81
53 Personal care workers	6.38
54 Protective services workers	0.45
6 Skilled Agricultural, Forestry and Fishery Workers	
61 Market-oriented skilled agricultural workers	0.49
62 Market-oriented skilled forestry, fishery and hunt	0.25
7 Craft and Related Trades Workers	
71 Building and related trades workers, excluding electricians	2.50
72 Metal, machinery and related trades workers	2.73
73 Handicraft and printing workers	0.05
74 Electrical and electronic trades workers	0.81
75 Food processing, wood working, garment and other	1.13
8 Plant and Machine Operators, And Assemblers	

81 Stationary plant and machine operators	1.51
82 Assemblers	0.32
83 Drivers and mobile plant operators	4.20
9 Elementary Occupations	
91 Cleaners and helpers	2.28
92 Agricultural, forestry and fishery labourers	0.32
93 Labourers in mining, construction, manufacturing	2.13
94 Food preparation assistants	1.13
96 Refuse workers and other elementary workers	0.00
91 Cleaners and helpers	0.62

Weighted pct. Unweighted N=970. Filter: A5=1. Missing=61.

A7-A9. When thinking about your current main job and your main paid job in 2016 are these then:

	Yes	No	Don't know
At the same employer?	76.32	23.61	0.06
At the same workplace?	71.67	28.27	0.06
The same position?	76.86	23.07	0.06

Weighted pct. Unweighted N=1031. Filter: A1=" Yes" and A5=" Yes".

B. Work Organization

The following questions concern work organization in your main job.

B1.-B11. How often does your job involve?							
	Always	Often	Some-times	Rarely	Never	Refuse	Don't know
Meeting precise quality standards?	50.32	28.90	11.40	5.36	3.34	0.11	0.58
Assessing yourself the quality of your own work?	42.30	42.71	9.66	3.08	1.89	0.11	0.24
Solving unforeseen problems on your own?	35.83	49.10	12.22	2.12	0.63	0.11	-
Monotonous tasks?	8.64	21.63	36.98	25.44	7.20	0.11	-
Complex tasks	14.59	45.55	30.36	7.76	1.26	0.11	0.37
Learning new things?	12.75	45.33	32.62	8.16	0.91	0.22	-
Short, routine and repeated tasks of less than 10 minutes?	6.64	27.76	29.02	23.79	12.24	0.22	0.33
Rotating tasks between yourself and colleagues?	15.35	41.26	26.58	11.23	4.88	0.22	0.47
That you are able of choose or change your methods?	18.52	37.26	28.19	11.92	3.62	0.22	0.27
That you have the option to change your speed at work?	21.89	34.78	22.95	14.90	4.66	0.22	0.60
That you work in group or team that has common tasks and plan its work?	22.39	34.84	21.60	12.57	7.96	0.22	0.41

Weighted pct. Unweighted N=1121. Filter: A1=" Yes".

B12.-B15. How often does your pace of work depend on?							
	Always	Often	Some-times	Rarely	Never	Refuse	Don't know
The work done by colleagues?	8.11	28.48	32.25	20.83	9.83	0.22	0.27
Measurable production targets or performance targets?	16.15	24.94	23.02	20.10	15.02	0.22	0.54
Automatic speed of a machine or movement of a product?	7.19	9.97	9.20	15.07	57.89	0.29	0.39
Direct control of superiors?	3.79	9.55	25.80	35.78	24.70	0.29	0.09

Weighted pct. Unweighted N=1121. Filter: A1=" Yes".

C. Organization

C1.-C5. Compared to your main job in 2016, does your current main job more or less often involve?	More often	Less often	Unchanged	Refuse	Don't know
Solving unforeseen problems on your own?	30.84	5.33	63.43	0.29	0.10
Complex tasks?	28.23	7.76	63.63	0.29	0.10
Short, routine and repeated tasks of less than 10 minutes?	11.43	19.22	68.63	0.36	0.36
That you are able to choose or change your methods of work?	22.53	9.51	67.48	0.36	0.11
That you have the option to change your speed of work?	21.91	10.87	66.82	0.36	0.04

Weighted pct. Unweighted N=1031. Filter: A1=" Yes" and A5=" Yes".

D. Job satisfaction

D1. On the whole, how satisfied are you with the working conditions in your main paid job?					
Very satisfied	**Satisfied**	**Not very satisfied**	**Not at all satisfied**	**Refuse**	**Don't know**
42.19	46.30	9.63	1.43	0.36	0.09

Weighted pct. Unweighted N=1121. Filter: A1=" Yes".

D2.-D4. How much do you agree or disagree with the following statements describing some aspects of your main job?

	Strongly agree	Agree	Neither/Nor agree	Disagree	Strongly disagree	Refuse	Don't know
I might lose my job in the next 6 months	2.24	4.61	10.47	24.84	56.72	0.42	0.67
Considering all my efforts and results in my job I feel that I am paid justly	8.22	39.82	20.96	22.83	8.07	0.43	0.11
My job offers good prospects for career advancement	8.95	36.51	30.15	16.49	7.06	0.43	0.41

Weighted pct. Unweighted N=1121. Filter: A1=" Yes".

E. Social Interaction

The following questions concern interaction with colleagues and others in the job.

E1-E4. In your main job how often do you usually...	**Every day**	**At least once a week**	**1-3 times a month**	**Less than once a month**	**Never**	**Refuse**	**Don't know**
... advice, instruct, train or teach people individually or in groups?	23.50	22.67	17.20	25.50	10.32	0.43	0.38
... sell a product or sell a service?	20.91	6.09	5.01	8.62	58.78	0.36	0.23
... negotiate contracts or terms more generally with people inside or outside your firm or organisation?	4.72	5.01	8.80	18.86	62.19	0.41	0.00
... share work related information with people inside or outside your firm or organisation?	35.94	20.97	12.77	11.27	18.01	0.41	0.63

Weighted pct. Unweighted N=1121. Filter: A1=" Yes".

E1A-E4A. Compared to your main job in 2016 does your current main job entail that you more or less often...	**More often**	**Less often**	**Unchanged**	**Refuse**	**Don't know**
... advice, instruct, train or teach people individually or in groups?	24.21	11.11	63.82	0.36	0.50
... sell a product or sell a service?	8.73	8.10	82.63	0.36	0.18
... negotiate contracts or terms more generally	8.55	6.38	84.32	0.41	0.34

with people inside or outside your firm or organisation?					
... share work related information with people inside or outside your firm or organisation?	15.17	4.82	79.07	0.41	0.53

Weighted pct. Unweighted N=1031. Filter: A1=" Yes" and A5=" Yes".

E1B-E4B. How have you primarily acquired the skills to...					
	By formal training such as classroom and online courses	**Training by peers at work such as experienced colleagues and supervisors**	**Own learning-by-doing, possibly using teaching materials such as books, videos etc.**	**Refuse**	**Don't know**
... advice, instruct, train or teach people individually or in groups?	22.88	30.24	46.86	-	0.02
... sell a product or sell a service?	19.59	33.00	46.51	0.44	0.46
... negotiate with people inside or outside your firm or organisation?	18.91	31.58	49.51	-	-
... share work related information with people inside or outside your firm or organisation?	17.71	31.34	50.17	-	0.78

Weighted pct. Unweighted N: [E3B, E4B, E1B, E2B]=[740, 323, 217, 782]. Filter: [E3, E4, E1, E2]=" Every day", "At least once a month" or "1-3 times a month".

E1C-E4C. To what extent do you feel that you have the skills to perform this activity at the level required in the main job?

	To a high extent	To some extent	To a lesser extent	Not at all	Don't know
... advice, instruct, train or teach people individually or in groups?	65.70	32.91	1.17	0.22	-
... sell a product or sell a service?	65.96	28.29	5.39	0.36	-
... negotiate with people inside or outside your firm or organisation?	56.28	39.99	2.77	0.97	-
... share work related information with people inside or outside your firm or organisation?	63.80	30.30	4.49	0.97	0.43

Weighted pct. Unweighted N: [E3C, E4C, E1C, E2C] = [740, 323, 217, 782]. Filter: [E3, E4, E1, E2] =" Every day", "At least once a month" or "1-3 times a month".

F. Robots

The following questions concern the use of robots in your job. A robot is a programmable and movable machine, which performs tasks in manufacturing or services. Robots can be stationary using an arm for example doing welding, assembling or packing, or they can be mobile robots for example doing cleaning, maintenance or warehouse work.

F1-F2. In your main job how often do you usually...							
	Every day	**At least once a week**	**1-3 times a month**	**Less than once a month**	**Never**	**Refuse**	**Don't know**
...deliver inputs or receive output such as raw materials, final goods or semi-manufactures to or from a robot?	4.62	2.13	1.18	3.08	88.06	0.48	0.45
... start, monitor and stop a robot to accomplish a specific task?	3.62	1.43	1.79	3.06	89.51	0.48	0.10

Weighted pct. Unweighted N=1121. Filter: A1=" Yes".

F1A-F2A. Compared to your main job in 2016, does your current main job entail that you more or less often...					
	More often	**Less often**	**Unchanged**	**Refuse**	**Don't know**
...deliver inputs or receive output such as raw materials, final goods or semi-manufactures to or from a robot?	3.46	2.07	93.31	0.41	0.74
... start, monitor and stop a robot to accomplish a specific task?	3.41	2.51	93.26	0.54	0.28

Weighted pct. Unweighted N=1031. Filter: A1=" Yes" and A5=" Yes".

F1B-F2B. How have you primarily acquired the skills to...

	By formal training such as classroom and online courses	Training by peers at work such as experienced colleagues and supervisors	Own learning-by-doing, possibly using teaching materials such as books, videos etc.	Refuse
...deliver inputs or receive output such as raw materials, final goods or semi-manufactures to or from a robot?	14.56	66.99	18.45	-
... start, monitor and stop a robot to accomplish a specific task?	5.38	83.02	9.90	1.70

Weighted pct. Unweighted N=[F1B, F2B]=[93, 77]. Filter: [F1, F2]=" Every day", "At least once a month" or "1-3 times a month".

F1C-F2C. To what extent do you feel that you have the skills to perform this activity at the level required in the main job?					
	To a high extent	**To some extent**	**To a lesser extent**	**Not at all**	**Refuse**
...deliver inputs or receive output such as raw materials, final goods or semi-manufactures to or from a robot?	48.11	40.79	7.60	3.49	-
... start, monitor and stop a robot to accomplish a specific task?	59.45	34.89	3.95	-	1.70

Weighted pct. Unweighted N=[F1C, F2C]=[93, 77]. Filter: [F1, F2]=" Every day", "At least once a month" or "1-3 times a month".

G. Advanced technologies

The following questions focus on the use of advanced technologies such as artificial intelligence, machine learning and internet connected sensors in your job. Such systems are programmed in so-called algorithms and they can be taught and learn continuously by feeding data and information in the form of observations and signals from sensors. The tasks performed by the systems include analysis and recognition of patterns in pictures, sound or text, and they are often able to improve their learning over time in an independent fashion.

G1-G3. In your main job how often do you usually...							
	Every day	**At least once a week**	**1-3 times a month**	**Less than once a month**	**Never**	**Refuse**	**Don't know**
... make use of information compiled automatically for you by a computer or by computerized machinery for making decisions or for advising clients or customers?	12.56	5.44	4.54	8.42	68.16	0.59	0.29
... receive orders or directions generated automatically by a computer or by computerized machinery?	7.90	3.24	2.82	7.26	77.59	0.59	0.60
... use a computer or computerized machinery that has the ability to automatically learn and improve from experience?	9.15	2.87	2.33	6.11	78.25	0.59	0.69

Weighted pct. Unweighted N= 1121. Filter: A1=" Yes".

G1A-G3A. Compared to your main job in 2016 does your current main job entail that you more or less often ...					
	More often	**Less often**	**Unchanged**	**Refuse**	**Don't know**
... make use of information compiled automatically for	10.24	2.56	86.21	0.54	0.44

you by a computer or by computerized machinery for making decisions or for advising clients or customers?					
... receive orders or directions generated automatically by a computer or by computerized machinery?	6.77	2.05	89.57	0.54	1.06
... use a computer or computerized machinery that has the ability to automatically learn and improve from experience?	6.76	2.43	89.04	0.54	1.23

Weighted pct. Unweighted N=1031. Filter: A1=" Yes" and A5=" Yes".

G1B-G3B. How have you primarily acquired the skills to...

	By formal training such as classroom and online courses	Training by peers at work such as experienced colleagues and supervisors	Own learning-by-doing, possibly using teaching materials such as books, videos etc.	Refuse	Don't know
... make use of information compiled automatically for you by a computer or by computerized machinery for making decisions or for advising clients or customers?	25.36	44.71	29.93	-	-
... receive orders or directions generated automatically by a computer	24.98	49.37	25.11	0.54	-

or by computerized machinery?					
... use a computer or computerized machinery that has the ability to automatically learn and improve from experience?	24.52	32.72	41.03	0.48	1.25

Weighted pct. Unweighted N=[G1B, G2B, G3B]=[265, 164, 171]. Filter: [G1, G2, G3]=" Every day", "At least once a month" or "1-3 times a month".

G1C-G3C. To what extent do you feel that you have the skills to perform this activity at the level required in the main job?						
	To a high extent	**To some extent**	**To a lesser extent**	**Not at all**	**Refuse**	**Don't know**
... make use of information compiled automatically for you by a computer or by computerized machinery for making decisions or for advising clients or customers?	55.29	38.24	5.61	0.85	-	-
... receive orders or directions generated automatically by a computer or by computerized machinery?	58.92	31.20	5.42	4.16	0.30	-
... use a computer or computerized machinery that has the ability to automatically learn	46.03	44.67	5.60	2.47	0.48	0.75

and improve from experience?

Weighted pct. Unweighted N=[G1C, G2C, G3C]=[265, 164, 171]. Filter: [G1, G2, G3]=" Every day", "At least once a month" or "1-3 times a month".

H. Job seekers

H1–H4. **In the following there is a list of statements. Please indicate to which degree you agree with each statement.**

	Strongly agree	Agree	Neither/Nor agree	Disagree	Strongly disagree	Refuse	Don't know
My skills are obsolete compared to the jobs being offered.	0.29	9.27	21.50	29.42	32.78	-	6.74
I receive the necessary continuing education such that I can fill the jobs being offered.	7.22	25.29	7.38	6.94	46.52	-	6.65
My union helps me acquire the skills required for me to find employment again.	5.85	13.26	7.18	10.23	52.06	-	11.43
Government assistance helps me acquire the skills necessary for me to find employment again.	7.96	13.09	10.93	9.80	47.33	-	10.88

Weighted pct. Unweighted N=115. Filter: A1=" No".

J. Ending

J1. In which municipality do you have your official address?	
Copenhagen	13.82
Copenhagen Environs	10.12
North Zealand	8.15
Bornholm	0.85
East Zealand	3.41
West and South Zealand	10.20
Funen	8.07
South Jutland	12.26
East Jutland	17.10
West Jutland	6.03
North Jutland	9.98

Weighted pct. Unweighted N= 1213. Missing=31.

	Yes, doing it now	Yes, but not doing it anymore	No	Refuse	Don't know
J2. Have you ever established and managed your own business, either alone or together with others?	5.37	11.03	82.50	0.80	0.29

Weighted pct. Unweighted N= 1244.

J3. If there were a general election tomorrow, which political party would you most likely vote for?	
Socialdemokratiet	17.99
Dansk Folkeparti	6.41
Venstre	13.14
Enhedslisten	4.32

Liberal Alliance	3.15
Alternativet	2.27
Radikale Venstre	6.71
Socialistisk Folkeparti	4.79
Det Konservative Parti	3.44
Kristendemokraterne	0.69
Nye Borgerlige	1.15
Other political party	1.21
Don't know	29.13
I would not vote	1.97
I cannot vote	1.83
Refuse	1.79

Weighted pct. Unweighted N= 1244.

Appendix 2 Methods

An introduction to the Technology and Skills (TASK) survey is given in box 1 in the main text and further details are elaborated in this appendix. The survey was primarily funded by the Aalborg University Social Science Talent Programme for Younger Researchers and additional funding was obtained through the ReDy project, which was funded by the Obel Family Foundation.

The TASK questionnaire was developed over 2018 with inspiration from Eurofound's European Working Conditions Survey (EWCS) and OECD's Programme for the International Assessment of Adult Competences (PIAAC) survey to ensure comparability.

The questionnaire for the TASK survey was developed in late 2018 in collaboration with Statistics Denmark (DST), who also ran a pilot survey to test the questionnaire. The questionnaire was developed with inspiration from Eurofound's European Working Conditions Survey (EWCS) and OECD's Programme for the International Assessment of Adult Competences (PIAAC) survey to ensure comparability. The unique questions on the use of new technologies (blocks F and G) where developed specifically for TASK. DST then collected the data in the spring of 2019 through a web-based survey distributed through the public e-mail system 'E-boks', and telephone interviews. The sample was created from DST's registries in late 2018 as described below.

Population

The relevant population consists of 2,076,617 observations. Each observation is a person with an employment relation to a workplace as described in the following.

The starting point for constructing the population is DST's register of employment relations in Denmark in November 2018. For each person, the employment relation with the most working hours or latest end date was chosen. Observations in the bottom decile for hours worked or wage income in November 2018 are excluded. This means people working less than 17.09 hours or earning less than 2727 DKK (approximately 365 Euros).

The result was 2,651,297 observations, which were then merged with DST's registry for businesses in the third quarter of 2018 by workplace. Observations that could not be merged were excluded. Observations connected to workplaces with less than 5 full time equivalent employees on average over the previous four quarters, and observations connected to workplaces in industry "O Public administration and defence" were also removed. Finally, the dataset is limited to individuals in the population of Denmark on 31 December 2018 who are at least 18 years old on 1 March 2019.

This results in the final population of 2,076,617 observations of employees.

The sample

The gross sample consists of 3162 randomly selected observations from the population.

The population was divided into ten strata by the address and size of the workplace. The ten strata are defined by the five administrative regions of Denmark and two size groups: 5-49 fulltime equivalent employees and 50+ fulltime equivalent employees. 2/3 of the sample are drawn from the five strata for workplaces of 50+ employees. The sample is proportional to the population across the regions.

45 individuals were not contacted because of protected address, unknown address, death or emigration. The remaining 3117 observations is the net sample.

Dataset and post stratification weights

1244 individuals responded to the survey, which means that the response rate is 39.9 percent. 65.4 percent of the responses were obtained through the web-based questionnaire while the remaining 34.6 percent were obtained through telephone interviews.

DST supplies post stratification weights based on gender (two categories), age (three categories), wage (two categories) and education (three categories) by each of the ten strata, allowing statistics constructed from TASK to be representative for the population.