Chapter 8: The impact of robots and AI/ML on skills and work organization[[1]](#footnote-1)

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**Abstract**

The chapter focuses on how new automation technologies are affecting the skills of employees and their form of work organization. The analysis makes use of unique data from the 2019 Danish TASK Survey carried out at the employee level which includes measures work organization, skills gaps and forms of training for employees using robots, artificial intelligence and machine learning (AI/ML) in their daily work activity. The analysis goes deeper into the effects of robotics and AI/ML for individual workers than previous studies and has policy implications for the performance of the Danish national system of innovation by identifying sectors and occupations that could potentially benefit from increased investments in training for skills development.

# 1 Introduction

A large amount of high-quality research has been undertaken on the consequences of the diffusion of robotics for wages, for the income distribution and for employment (Autor et al. 2003; Goos and Manning 2007; Goos et al. 2014; Brynjolfson and McAffee 2015; Acemoglu and Restrepro 2018; OECD 2017; Graetz and Michaels 2018). Such studies often use relatively aggregate data and often relatively dated data in the interest of obtaining high coverage and high-quality data. Few studies are able to take into account the significant recent changes that have emerged along with collaborative robots (cobots) and the integration of robots with artificial intelligence and machine learning, or the more recent diffusion of artificial intelligence (AI) and machine learning (ML) more generally in the economy. There is thus a need to expand the study of robots with micro level data (as also pointed out by Seeman and Raj 2018). Furthermore, as pointed out by Brynjolfson et al. 2018, there is a need to study ML intensively, as it is becoming a general-purpose technology, and its impact on job re-design and task bundles will be widespread.

Like ML, the diffusion of robots is picking up pace. According to data from the International Federation of Robotics (IFR) the number of industrial robots (an automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes, ISO 8373) sold worldwide exceeded 400.000 for the first time in 2018 (IFR 2019a). Most of these (65%) installed in the automotive, electrical/electronics, and metal and machinery industries. This suggests broader diffusion of robots, and so does the rapid increase in sales of professional service robots (performs useful tasks for humans or equipment excluding industrial automation applications, ISO 8373) which increased by 60% from 2017 to 2018, where worldwide sales were 111.000, and this yearly growth rate is expected to continue (IFR 2019b). In Denmark, the share of private sector firms using robots increased from 10 to 12 percent from 2018 to 2019, while the increase in firms using AI or ML was from 5 to 6 percent (DST 2020). In relative terms, this is a 20% increase for both robotics and AI/ML in one year.

The increased rate of automation both within and across sectors and industries has certainly contributed to boost productivity, although with diminishing gains (Graetz and Michaels 2018), but has also raised concerns regarding job losses, job polarization and income inequality (Brynjolfson and McAffee 2015; Acemoglu and Restrepro 2016; OECD 2017). The acceleration of automation is posing new demands for skill formation on firms and at the national level (Pinzone et al. 2017; World Economic Forum 2018). To achieve the full productivity potential of robots and AI/ML, the workforce must be equipped with necessary skills supported by changing modes of work organization. This creates both opportunities and challenges for the national innovation system. New opportunities emerge to develop, produce, install and maintain such new technologies, and other challenges emerge in terms of the effects on workers. New technologies require adaptation of the skills of the workforce which can be facilitated by labor market policy and the training and education system (Nielsen et al. 2020 [other chapter]). This aspect of the so-called Industry 4.0 revolution has been somewhat neglected in the literature compared to the number of contributions focusing on the negative ramifications mentioned above.

On this background, the purpose of the chapter is to strengthen knowledge on how automation technology has affected the skills of employees and work organization. The case of Denmark could be especially interesting in this regard for at least a couple of reasons. Firstly, because Denmark is a leading country outside Asia regarding development and dissemination of robot technology (Graetz and Michals 2018), which might have contributed to furthering the dissemination and adaptation of skills. Secondly, there exists a positive stance among Danish employer and employee organizations towards adopting robots and AI/ML to exploit the potential in the new technologies. This collaborative approach among labor market organizations can potentially have led to a more rapid spread of technologies and skills in the Danish labor market by mitigating the fears of job losses and restructuring. As an example of labor unions positively embracing technological change, one could mention that The Danish Metal Workers Union has proposed a robot strategy (Dansk Metal 2019) with a number of suggestions as to how this technology could be applied to strengthen productivity and competitiveness. The Danish case thus contains some systemic characteristics, which makes it especially interesting.

As described in more detail below, the analysis in this chapter uses new data from the Danish TASK Survey 2019, which consist of employee survey data on skills, work organization and the use of robots, AI and ML at work for a representative stratified sample of the Danish workforce. Our new and unique data gives us the opportunity overview key issues of policy importance. It allows us to go deeper into effects of robotics for individual workers than previous studies, and it allows us to compare the effects of robotics to the effects of AI and ML.

The chapter is structured as follows. In section 2, we provide a detailed account of the TASK Survey data and use cluster analysis to develop a taxonomy of forms of work organization. Section 3 presents the dissemination of working tasks involving robot technology as well as AI/ML, supplemented by a mapping of related skill gaps and their causes. We then proceed in section 4 to shed light on the predictors of diffusion and skill gaps for workers utilizing the two types of technologies in a series of logistic regression models. Finally, in section 5, we conclude and discuss the implications for general educational policies as well as policies for continued education and training.

# 2 Data: The TASK survey

We use data from a Danish survey on technologies and skills (TASK) undertaken in the spring of 2019. The survey was carried out by researchers from the IKE group at Aalborg University together with Statistics Denmark.[[3]](#footnote-3)

The TASK survey covered individual employees in Denmark. Registry data from November 2018 covering the entire population of Denmark was used to delimit the relevant population and for the sampling frame. The main paid job of each individual was identified and only wage earners were included in the population. People employed at workplaces of less than five full time equivalent employees (FTEs) or at workplaces with a NACE code for public sector administration were excluded. The result was a population of 2,076,617 employees in Denmark and from this population a stratified sample of 3,117 employees was drawn. The sample was stratified in ten strata defined by the five NUTS2 regions of Denmark and whether the workplace of the employees had less than 50 FTEs or 50+ FTEs. In the population, close to half of all individuals are in workplaces with 50+ FTEs and half are in workplaces of less than 50 FTEs. However, as the questions explored in the survey – in particular work organization and the use of robots and other advanced technologies – were assumed to be more relevant for larger workplaces, and workplaces in Denmark are relatively small, larger workplaces were oversampled. Thus, two thirds of the sample are in the five strata of 50+ FTEs.

The survey was initially administered through the platform for digital communication used in communication between the Danish public sector and the public (e-Boks), and followed up by phone interviews to boost the response rate. The result was 1,244 full responses or a response rate of 39.9 percent and an additional 145 partial responses. Statistics Denmark finally produced post stratification weights to make the data representative by each of the ten strata according to gender, age, wage and education, and to correct for the oversampling of employees at large workplaces.

In addition to the responses from the TASK survey the dataset created by Statistics Denmark contains a handful of variables copied from the registry data: industry of workplace (10 groups), wage (four groups), age (three groups), and education (three groups).

## Work organization in Denmark

Earlier work (Lorenz and Valeyre 2007; Holm et al. 2010; Holm and Lorenz 2015) used data from the European Working Conditions Survey (EWCS) to study the characteristics of work organization. To build further on this work the TASK survey included the same questions on work organization as the EWCS, with only minor necessary changes identified in the pilot survey, and with additional retrospective questions regarding changes in work organization over time.

For the analysis presented here we make use of 14 of these questions. In the survey the respondents are asked how often they experience each work organization characteristic on a five-level scale, from which we create binary variables taking the value 1 of the respondent experiences the characteristic “always” or “often”. The 14 binary variables are then subjected to a multiple correspondence analysis (MCA) and the first two factors are used to identify distinct forms of work organization. Table 1 lists the 14 characteristics and reports the share of respondents experiencing the characteristic by work organization cluster, as explained below.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variables | DL | Lean production | Simple  organization | Average |
| Discretion in fixing work methods | **73.7** | **62.2** | 19.0 | 55.8 |
| Discretion in fixing work pace | **73.4** | 49.5 | 30.2 | 56.7 |
| Learning new things in work | **72.3** | **76.2** | 20.7 | 58.1 |
| Problem solving activities | **93.4** | **91.5** | 65.4 | 84.9 |
| Complexity of tasks | **73.6** | **76.3** | 25.5 | 60.1 |
| Responsibility for quality control | **90.3** | **90.4** | 72.1 | 85.0 |
| Respect for quality norms | 69.3 | **95.7** | **87.1** | 79.2 |
| Teamwork | **62.8** | **80.8** | 32.3 | 57.3 |
| Job rotation | **58.0** | **81.9** | 38.2 | 56.6 |
| Repetitiveness of tasks | 18.8 | **55.3** | **49.9** | 34.4 |
| Horizontal constraints on work rate | 26.7 | **74.2** | 31.2 | 36.6 |
| Norm-based constraints on work rate | 28.2 | **89.9** | 34.3 | 41.12 |
| Automatic constraints on work rate | 2.9 | **48.7** | **23.7** | 17.2 |
| Hierarchical constraints on work rate | 4.3 | **37.3** | **15.0** | 13.3 |
| Total | 53.0 | 18.1 | 28.9 | 100.0 |

Pct. experiencing each characteristic

Table 1. Work organization clusters

The interpretation of the clusters builds directly on Lorenz and Holm (this volume). Clustering based on the first two factors of the MCA yields a three-cluster solution representing stylized forms of work organization. The shares of employees grouped in first and second clusters are both above the population average on work organization characteristics indicating continuous learning on the job. This means learning new things, having complex tasks and engaging in problem solving. However, in the second cluster, this is combined with above average presence on constraints on the work pace or rate. This includes, horizontal, norm-based, automatic and hierarchical constraints, while in the first cluster high rate of learning are combined with below average constraints and also with relatively high levels of autonomy in setting work pace and choosing work methods. The second cluster captures jobs characterized by learning but in a relatively tightly structured mode. We refer to this as Lean work organization. The first cluster captures jobs characterized by learning, autonomy and few constraints. We refer to this as discretionary learning (DL) work organization. The third and final cluster is located in-between the first two clusters when considering constraints in the jobs. Workers in the third cluster also tend to score low on variables indicating autonomy and continuous learning in the job. This corresponds to relatively traditional jobs with limited skill development in the job and a combination autonomy and constraints depending on the specific task in question. We refer to this as Simple work organization.

According to the TASK survey, roughly half (53%) of the employees in Denmark have DL forms work organization, 18% have Lean work organization and the remaining 29% has Simple work organization. These numbers are not directly comparable with the earlier studies cited above based on EWCS data which were restricted to private sector establishments. The analysis here using the TASK survey data has a broader coverage including both the education and health sectors.[[4]](#footnote-4)

# 3 Describing new technology use

When describing new technology use in jobs in Denmark five questions on the TASK survey are central. These all ask the respondent to indicate how often her job involves specific tasks:[[5]](#footnote-5)

1. deliver input or receive output such as raw materials, final goods or semi-manufactures to or from a robot
2. start, monitor and stop a robot to accomplish a specific task
3. make use of information compiled automatically for you by a computer or by computerized machinery for making decisions or for advising clients or customers
4. receive orders or directions generated automatically by a computer or by computerized machinery
5. use a computer or computerized machinery that has the ability to automatically learn and improve from experience

The first two tasks relate to robots and the final three tasks relate to artificial intelligence (AI) and machine learning (ML). In the detailed analysis later in the chapter we distinguish between all five tasks but initially we present a simple overview indicating the share of workers using robots or AI/ML in some manner in their job. We thus initially collapse the first two into one indicator for using robots and the final three into one indicator for using AI/ML. While this has the advantage that our robot indicator, for example, captures the use of robots in a broad sense, it has the disadvantage of ignoring differences in the ways robots may be used in a firm. This is mended in the later econometric analysis.

An employee uses robots (AI/ML) if she performs at least one of the first two (final three) tasks at least weekly. In addition to whether an employee performs a task or not in 2019, we are also interested in whether she has experienced an increased in the frequency of the task since 2016, whether she has the necessary skills for the task and the main mechanism used for acquiring skills for the task.

An employee has seen an increase in tasks related to robots (AI/ML) if she reports an increase in at least one of the first two (final three) tasks over the last three years. An employee has a skill gap for robots (AI/ML) if she does not have the skills for performing at least one of the first two (final three) tasks 'to a high extent', conditional on performing the task. The TASK survey allows the respondent to indicate one main mechanism for acquiring skills for each task that she performs. The possible mechanisms are formal training, peer learning and self-taught. An employee has used one mechanism for acquiring skills related to robots (AI/ML) if she reports to have used only that mechanism for the first two (final three) tasks conditional on performing the task. If she indicates different mechanisms on the first two (final three) tasks, then her mechanism for acquiring skills is ‘a combination’.

## The use of robots

Figure 1 shows according to occupation, sector and the form of work organization the relative proportion of employees that use robots, the relative proportion that experience a skill gap and the relative proportion that have seen an increase in the use of robots over the preceding three years. The proportions are relative to the national average so that a value of 2 indicates twice the national average. At the national level, 8.27 percent of employees use robots, of these 50.04 percent have a skill gap and 5.22 percent have seen an increase in the use of robots from 2016 to 2019.

The left-hand side shows the use of robots by occupation, the centre shows the distribution by industry and the right-hand side shows the distribution by work organization. For example, the left-hand side shows that the use of robots by plant and machine operators is slightly over twice the national average of 8.27 percent. The other two occupations with relatively high penetrations of robot use are also occupations often associated with manufacturing: elementary occupations and technicians. However, as opposed to manufacturing as a whole, these three groups have below average skill gaps.

The centre shows unsurprisingly that robots are most commonly used in the manufacturing industry where the diffusion is more than twice the national average of 8.27 percent as shown by the dots connected with a solid line. Notice that the groups are ordered in descending order by robot use. The increase in robot use in manufacturing is twice the national average (cf. the diamond) and the skill gap is at the national average (cf. the dots), which is however a seemingly high 50 percent.

Figure 1. Robot use in Denmark

A curious finding is that the finance industry seems to have robot penetration at the same level as manufacturing and an even stronger increase than manufacturing, but this likely to result from a measurement error as AI based computer programs are typically referred to as ‘robots’ in the finance industry. A more interesting observation is that craft workers have both the largest skill gaps and the largest increase in robot use, although the increase only brings them up to the national average. Relatedly, the construction industry is simultaneously the industry with the lowest robot penetration and one of the largest skill gaps, which probably reflects that robots are poorly adapted to the varied and changing physical conditions of worksites in the construction industry. It could also indicate that craft workers are insufficiently trained for using robots and that this is hampering the diffusion of robots in construction.

Some interesting but largely unexplainable results stand out. The culture and leisure industry has seen a large increase in robot use and employees in this industry have very low skill gaps, while the ICT industry is where the largest skill gaps are found. These results will be pursued further in the multivariate analysis that follows below.

While learning at work is one of the main differences between the forms of work organization, there does not seem to be any relationship between work organization and the proportion of workers that report skill gaps in using robots in their work. Robot use and the increase in robot use are both particularly high for employees with the Lean form of work organization and low for employees with DL work organization. It thus appears that the major difference lies in constraints at work: employees who work more often with robots have more constraints. These constraints are, however, also combined with both learning and complexity, which can mean that using robots at work makes the job more intrinsically gratifying.

## The use of AI/ML

Figure 2 is similar to figure 1 but describes the use of AI/ML rather than robots. At the national level 25.57 percent use AI/ML of which 50.75 percent have a skill gap and 11.27 percent have seen an increase in the use of AI/ML from 2016 to 2019.

The diffusion of AI/ML by occupational groups shows that the technologies are evenly diffused, cf. the left graph in figure 2. The share of employees using AI/ML is close to the national average in all groups. Interestingly, there is an almost perfect inverse relationship between the share that uses the technologies and the share that experiences a skill gap for the technologies when considering the occupational groups (cf. the steady increase in the bold dots when going left to right across occupational groups). A somewhat similar pattern seems to hold across the industry groups in the central part of figure 2. Either this implies a sort of externality where employees more often feel that they do not have sufficient skills for a technology when the technology is relatively exotic in their industry, or diffusion of the technology is hampered by a lack of skills among employees. Again, craft workers and the construction industry stand out as the occupational group and the industry group with particularly low diffusion and large skill gaps.

Not surprisingly, AI/ML is relatively widely diffused in the finance and ICT industries while increases in the use of AI/ML are seen across a wide range of industries. Interestingly, increases in AI/ML use by occupation are highest in occupations that are not traditionally considered highly skilled: Plant and machine operators and elementary occupations. However, neither group reports particularly high skill gaps for using AI/ML. This does not mean that there is no room for improvement as the national average for the skill gap is 50.75 percent.

Figure 2. AI/ML use in Denmark

Regarding work organization it can be observed again that both the greatest diffusion and the greatest increase in diffusion of AI/ML is seen for Lean work organization. As with the use of robots, this can imply that AI/ML technologies at work substitutes the dull tasks and leave employees with more interesting jobs characterised by continuous learning, while also imposing constraints on work. However, the opposite direction of causality is in principle also possible which would imply that employees with Lean forms of work organization have jobs that are relatively susceptible to automation with robots or AI/ML and thus that such employees necessarily must be adaptable or risk losing their jobs.

The differences by occupation, industry and work organization described in figures 2 and 3 are likely to be correlated. E.g. employees in construction may no longer have above average probability of a skill gap after correcting for the fact that many employees in construction are craft and related trades workers. Before using regression analysis to disentangle these effects we describe the relationships between skill gaps, training mechanisms and job security.

## Mechanisms for acquiring skills

Figure 3 shows the learning mechanisms used for the five questions on the use of new technology in work. The figure shows the percentage of employees using each mechanism as the main mechanism for skill acquisition by technology task, and the shares when considering only employees with a skill gap for the task. The two points are connected by a line segment and the slope of the line thus illustrates whether the learning mechanism is relatively more or less common among workers with a skill gap. If a learning mechanism is relatively less common among workers with a skill gap (negative slope) then the mechanism appears to mitigate skill gaps, and vice versa.

The solid line is the top line for all tasks except ML tasks which means that peer learning is the main mechanism for skill acquisition in all other cases. For controlling robots, the share reporting peer learning as the main mechanism for skill acquisition is around 85%. Peer learning is generally used more often for acquiring robot related skills than for acquiring AI related skills. For all five skills the least used mechanism for skill acquisition is formal training (dotted line). At the same time, it seems that formal training is reported less often as the most important mechanism for employees with a skill gap (ie. the dotted lines all have negative slope). This indicates that relying on formal training as the main mechanism for skill acquisition is associated with the absence of skill gaps. Correspondingly, the dashed lines for the skill acquisition mechanism ‘own learning-by-doing’ consistently has a positive slope indicating that employees with a skill gap relatively often have had own LBD as the main mechanism for skill acquisition. This pattern of course only indicates that own LBD is associated with skill gaps when own LBD is the main mechanism for skill acquisition. Own LBD may very well still be a good complement to other training forms.

Figure 3. Learning mechanisms

The most pervasive learning mechanism – training by peers – seems to have varying associations with skill gaps. Training by peers is associated with less likelihood of skill gaps for controlling robots and for taking directions from AI (ie the slope is negative) but associated with a higher likelihood of skill gaps for using data from AI and for using ML. In Nielsen et al. (this volume) it is emphasized that experience-based learning is important when employees face novel technologies and the descriptive results here partially contradict this by showing a positive relationship with formal training. However, it must be emphasized that figure 3 focusses on the ‘main’ mechanism, and that the figure only reports a bivariate relationship. Learning mechanisms are not context free; what works in manufacturing may not work very well in the finance industry. The result is thus likely to change in the below multivariate analysis.

# 4 Regression analyses

In this section we report two times five logistic regressions. The first five models are based on the full dataset and predict, respectively, whether or not the employee has one of the five technology related tasks: working alongside robots, controlling robots, using data from AI, taking directions from AI and using ML. In all five cases “using” means using at least weekly. The next five models rely on subsets of the data, as they seek to predict skill gaps for the five tasks, and skill gaps can only be defined for employees actually having the relevant task. Having a skill gap is a binary variable taking the value 1 if the respondent reports to only have the necessary skills for the task to ‘some’ degree or less.

In all regressions we use the weights supplied by Statistics Denmark for the TASK survey and we cluster the standard errors by the strata of the survey. In all regressions we have only categorical regressors. We use weighted effect coding instead of the more common reference coding as we are not interested in the difference between each category and a specific reference category, but rather in the difference relative to the average observation, as in figures 1 and 2 above.[[6]](#footnote-6)

## Using technologies

The five variables for having tasks at work involving the use of robots, AI or ML are regressed on the variables from figures 2 and 3: occupation, industry and work organization. In addition, we control for age as a proxy for experience, wage as a proxy for position in the organizational hierarchy, employment level at the workplace and region. The results are presented in table 2 and show that four of the five tasks are positively associated with Lean work organization. Thus, the positive association between AI/ML and Lean in figure 2 is reproduced but the positive relationship between robots and Lean in figure 1 only pertains to controlling robots. The results are consistent with both robotics technologies and AI/ML technologies involving new knowledge acquisition (learning) but also intensification of work pace.

There is no statistically significant difference in work organization for people working alongside robots. Similarly, the strong associations between industry and robots, and occupation and robots only pertain to controlling robots. It thus seems like working alongside robots is more broadly diffused than controlling robots. This can be explained by workers in diverse sectors working alongside service robots rather than industrial robots.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Dependent variable: *Work with….* | | | | |
|  |  | | | | |
|  | With robots | Controls robots | AI data | AI instr. | ML |
|  | | | | | |
| DL | -0.224 | -0.360 | -0.035 | -0.191 | -0.083 |
|  | 0.384 | 0.392 | 0.166 | 0.217 | 0.200 |
| Lean | 0.653 | 1.014\*\* | 0.713\*\*\* | 0.977\*\*\* | 0.682\* |
|  | 0.544 | 0.510 | 0.272 | 0.368 | 0.370 |
| Simple | 0.054 | 0.108 | -0.372 | -0.216 | -0.255 |
|  | 0.601 | 0.716 | 0.286 | 0.396 | 0.406 |
| Size 50+ FTE | 0.070 | 0.036 | 0.065 | 0.111 | 0.048 |
|  | 0.207 | 0.187 | 0.104 | 0.140 | 0.152 |
| Size 5-49 FTE | -0.161 | -0.083 | -0.148 | -0.254 | -0.111 |
|  | 0.474 | 0.429 | 0.239 | 0.320 | 0.348 |
| Managers | 0.489 | 2.259 | -0.200 | -0.191 | -0.049 |
|  | 1.679 | 1.591 | 0.338 | 0.760 | 0.745 |
| Professionals | 0.038 | 1.064\* | -0.051 | -0.245 | -0.103 |
|  | 0.526 | 0.595 | 0.241 | 0.286 | 0.285 |
| Assoc. profs. & Techs | 0.289 | 2.151\*\*\* | -0.251 | 0.122 | -0.132 |
|  | 0.718 | 0.533 | 0.248 | 0.330 | 0.332 |
| Clerical support | -0.907 | -14.825\*\*\* | 0.854\*\* | 0.250 | -0.191 |
|  | 1.151 | 0.850 | 0.380 | 0.581 | 0.569 |
| Service and sales | -1.221 | 0.900 | 0.124 | 0.150 | 0.653 |
|  | 3.790 | 1.409 | 0.681 | 0.676 | 0.563 |
| Craft and related trades | 0.750 | 2.416\*\* | 0.305 | -0.473 | 0.043 |
|  | 1.153 | 0.956 | 0.646 | 0.742 | 1.107 |
| Plant and machine operators | 0.757 | 2.443\*\* | -0.077 | 0.656 | 0.108 |
|  | 0.908 | 1.015 | 0.621 | 0.737 | 0.474 |
| Elementary occupation | 0.276 | 2.779\*\* | -0.549 | 0.442 | 0.114 |
|  | 2.051 | 1.349 | 0.633 | 0.972 | 0.803 |
| Agriculture and fishing | -0.178 | -15.358\*\*\* | -1.452 | 0.496 | -13.596\*\*\* |
|  | 1.685 | 0.720 | 1.022 | 1.356 | 0.565 |
| Manufacturing and utilities | 1.189\* | 2.707\*\*\* | 0.566\* | 0.798\*\* | 0.386 |
|  | 0.658 | 0.598 | 0.291 | 0.374 | 0.321 |
| Construction | -1.633 | -15.824\*\*\* | -1.562 | -1.803 | -0.990 |
|  | 2.745 | 0.683 | 1.713 | 2.160 | 1.450 |
| Trade and transportation | 0.015 | 1.266 | 0.472 | 0.266 | -0.257 |
|  | 1.263 | 1.458 | 0.417 | 0.513 | 0.550 |
| ICT | 0.337 | -14.819\*\*\* | 1.727\*\*\* | -0.314 | 0.915 |
|  | 1.487 | 1.231 | 0.573 | 0.892 | 1.103 |
| Finance and insurance | 1.551\* | 2.840\*\*\* | 1.274\*\*\* | 1.431\*\*\* | 1.432\*\* |
|  | 0.834 | 0.886 | 0.376 | 0.510 | 0.707 |
| Business services | 0.513 | 1.307 | -0.381 | 0.697 | 0.200 |
|  | 0.809 | 0.892 | 0.336 | 0.487 | 0.407 |
| Teaching and health | -0.717 | 1.254\*\* | -0.450\* | -0.687\* | -0.056 |
|  | 0.905 | 0.582 | 0.231 | 0.367 | 0.231 |
| Culture, Leisure and other | 0.702 | 1.995\*\* | 0.038 | 1.447\*\* | 0.781 |
|  | 3.514 | 0.979 | 1.237 | 0.627 | 0.528 |
| Lowest wage quartile | -0.290 | -0.623 | -0.326 | -0.129 | -0.038 |
|  | 1.425 | 1.272 | 0.816 | 0.505 | 0.635 |
| Second wage quartile | 0.485 | 0.737 | -0.021 | 0.491 | 0.173 |
|  | 0.903 | 0.559 | 0.255 | 0.328 | 0.260 |
| Third wage quartile | 0.292 | -0.049 | 0.274 | 0.197 | 0.005 |
|  | 0.449 | 0.571 | 0.327 | 0.452 | 0.330 |
| Top wage quartile | -0.517 | -0.368 | 0.049 | -0.561\* | -0.163 |
|  | 0.570 | 0.794 | 0.300 | 0.316 | 0.346 |
| Age 18-39 | 0.211 | 0.177 | -0.105 | 0.130 | -0.183 |
|  | 0.677 | 0.801 | 0.251 | 0.379 | 0.349 |
| Age 40-59 | -0.071 | 0.064 | -0.002 | -0.121 | 0.082 |
|  | 0.316 | 0.384 | 0.116 | 0.185 | 0.173 |
| Age 60+ | -0.128 | -0.487 | 0.179 | 0.159 | 0.048 |
|  | 1.171 | 1.081 | 0.260 | 0.372 | 0.338 |
| Copenhagen City | 0.167 | -0.945 | -0.033 | -0.238 | -0.395 |
|  | 0.770 | 0.815 | 0.307 | 0.394 | 0.547 |
| Copenhagen Surroundings | 0.157 | 0.380 | -0.364 | -0.016 | -0.192 |
|  | 0.461 | 0.567 | 0.347 | 0.400 | 0.415 |
| North Zealand | 1.034 | 0.526 | 0.447 | 0.436 | 1.019\*\* |
|  | 0.718 | 0.566 | 0.489 | 0.706 | 0.501 |
| Bornholm | -13.916\*\*\* | 1.308 | 0.351 | 1.247\*\* | 0.759 |
|  | 1.892 | 1.328 | 2.567 | 0.558 | 0.875 |
| East Zealand | 1.570\*\* | 1.582\* | 1.532\*\*\* | 1.470\*\*\* | 0.332 |
|  | 0.740 | 0.943 | 0.500 | 0.476 | 0.620 |
| West and South Zealand | 0.162 | -0.216 | 0.050 | 0.297 | 0.054 |
|  | 1.541 | 0.772 | 0.452 | 0.514 | 0.671 |
| Funen | -0.310 | -0.412 | -0.386 | 0.102 | 0.041 |
|  | 0.759 | 0.855 | 0.495 | 0.810 | 0.536 |
| South Jutland | 0.440 | 0.253 | -0.083 | 0.120 | -0.187 |
|  | 0.406 | 0.691 | 0.331 | 0.638 | 0.328 |
| West Jutland | -0.353 | 0.566 | -0.037 | -0.851 | -0.384 |
|  | 2.843 | 2.398 | 0.515 | 0.810 | 0.616 |
| East Jutland | -0.532 | -0.138 | -0.103 | -0.635\* | 0.330 |
|  | 0.560 | 0.506 | 0.570 | 0.383 | 0.538 |
| North Jutland | 0.268 | 0.093 | 0.424 | 0.766\* | 0.028 |
|  | 1.350 | 0.771 | 0.384 | 0.453 | 0.501 |
| Constant | -3.369\*\*\* | -6.843\*\*\* | -1.726\*\*\* | -2.570\*\*\* | -2.206\*\*\* |
|  | 0.468 | 0.350 | 0.205 | 0.209 | 0.172 |
|  | | | | | |
| Observations | 1061 | 1062 | 1061 | 1057 | 1058 |
|  | | | | | |
| *Note:* | \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 | | | | |

Table 2. Models for using technologies and being afraid of losing the job for the complete dataset

Except for clerks using data from AI relatively often, the result that AI/ML technologies are evenly diffused across occupational groups is reproduced in table 2. The differences by industry are, however, more detailed compared to figure 2. AI appears to be relatively widespread in the manufacturing sector hinting at the growing integration of robotics and AI. While figure 2 showed equally high diffusion rates for AI/ML technologies in ICT and in finance, table 2 shows that there is a large difference: all three types of AI/ML tasks are relatively common in finance while in ICT it is only the task of using data from AI that is common. ICT firms may of course often be involved in developing AI/ML technologies, but this does not necessarily mean that such firms also use these technologies. The positive relationship with using AI generated data can reflect that specific ICT firms with online business models such as social media firms use AI/ML intensively. Workers in culture and leisure use AI/ML technologies often but only in the sense that they take directions from an AI. This may potentially include platform based personal services where customers are connected to independent contractors by an AI, cultural facilities such as libraries where AI systems determine the organization of books and other material, or betting and gambling firms where AI is used intensively.

No relationship between the size of the workplace and technology related tasks is found. This may be because our only available measure of size is relatively crude (above or below 50 fulltime equivalent employees (FTE)), or because the size measure is based on employment, which may in principle be decreased when automation technologies are diffused. Neither age nor wage has much effect on the likelihood of having tasks that include robots, AI or ML. This implies that there are no systematic differences in the hierarchical level or work experience of employees using these technologies. Finally, a number of regional controls are significant indicating that our variable for industry does not capture all regional heterogeneity in diffusion, or that regional differences in diffusion reflects more than just regional differences in industry structure. In particular, both robotics and AI are used relatively intensively in the region of East Zealand, which is an area just outside the capital city of Copenhagen well known for the concentration of large multinational companies (MNCs). North Zealand is another region just outside Copenhagen and here it seems that a disproportionate share of employees uses ML in their job. While East Zealand is characterized by many MNCs in general, North Zealand tends to be the location of pharmaceutical and chemical MNCs such as Bavarian Nordic, Chr Hansen, ALK Abello and Coloplast.[[7]](#footnote-7)

## Skill gaps

Skill gaps would ideally be regressed on the same variables as used in the previous section and, in addition, the training mechanisms of figure 3 and an indicator for the frequency of technology use. The frequency of technology use is relevant as the descriptive figures earlier suggested that, at the industry level, there is an inverse relationship between technology use and skill gaps. However, the number of observations for the models for skill gaps is limited by the fact that employees who do not use a given technology in their job cannot have a skill gap for that technology relative to the job’s requirement. It has therefore been necessary to construct the models stepwise and exclude variables that do not contribute to explaining skill gaps. Both the individual t-tests and the joint F-test were considered when dropping variables, and the same set of regressors has been used in both models for comparability.

Industry and region are therefore excluded in the five models for skill gaps presented in table 3. We are left with a model consisting of occupation, work organization, frequency of the relevant task, learning mechanism for acquiring skills for the relevant task, wage and age.

The descriptive analysis of figure 3 suggested that formal training is associated with a lower likelihood of skill gaps and this result is reproduced for two of the five tasks: formal training is associated with lower likelihood of skill gabs for controlling robots, and for using ML but not for the remaining three tasks. Based on figure 3 it was also expected that own LBD would be positively associated with skill gaps but this is only found for the task of controlling robots. While the training mechanism thus plays a role in skill formation for controlling robots, it is found that frequency of the task is an important predictor for skill gaps when working alongside robots, using data from AI or using ML. In all three cases, daily frequency is negatively associated with skill gaps while monthly frequency is positive for the last two. No statistically significant effects are found for work organization indicating that, while work organization does differ for workers with different tasks as shown earlier, this is not reflected in skill gaps. In particular, workers with technology related tasks are broadly more likely to have Lean work organization but this does not affect their proficiency for the technology related task.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Dependent variable*:* | | | | |
|  | *Skill gap for...* | | | | |
|  | With robots | Controls robots | AI data | AI instr. | ML |
|  | | | | | |
| Formal training | -1.056 | -2.719\*\* | -0.731 | 0.014 | -0.955\*\* |
|  | -0.811 | -1.063 | -0.465 | -0.412 | -0.464 |
| Peer learning | 0.038 | -0.456 | 0.302 | -0.044 | 0.019 |
|  | 0.220 | 0.278 | 0.203 | 0.323 | 0.297 |
| Own LBD | 0.518 | 5.577\*\* | 0.147 | 0.069 | 0.516 |
|  | 0.630 | 2.333 | 0.283 | 0.668 | 0.341 |
| Daily | -0.637\* | 0.116 | -0.391\*\* | -0.303 | -0.459\*\*\* |
|  | -0.364 | -0.576 | -0.182 | -0.315 | -0.132 |
| Weekly | 0.730 | -0.884 | 0.300 | 0.244 | 0.870\* |
|  | 0.726 | 1.306 | 0.371 | 0.628 | 0.475 |
| Monthly | 1.125 | 0.420 | 0.646\* | 0.457 | 0.824\*\* |
|  | 0.864 | 1.481 | 0.351 | 0.529 | 0.387 |
| DL | -0.174 | -0.220 | 0.004 | 0.060 | 0.177 |
|  | -0.524 | -0.626 | -0.208 | -0.246 | -0.236 |
| Lean | 0.299 | 0.858 | 0.217 | -0.124 | -0.291 |
|  | 0.927 | 1.071 | 0.399 | 0.586 | 0.470 |
| Simple | 0.171 | -0.083 | -0.143 | -0.046 | -0.182 |
|  | 0.955 | 1.209 | 0.407 | 0.418 | 0.466 |
| Managers | -0.167 | -3.863\*\* | -0.520 | -0.675 | -0.167 |
|  | -2.293 | -1.813 | -0.468 | -0.780 | -0.840 |
| Professionals | 0.569 | -0.858 | 0.378 | 0.657 | 0.388 |
|  | 0.859 | 0.988 | 0.267 | 0.425 | 0.359 |
| Assoc. profs. & Techs | -0.673 | 1.124 | 0.213 | 0.328 | 0.347 |
|  | 0.828 | 0.873 | 0.332 | 0.434 | 0.392 |
| Clerical support | -1.566 | -0.542 | -0.389 | -0.693 | -0.094 |
|  | 3.341 | 1.727 | 0.629 | 0.872 | 0.829 |
| Service and sales | 0.332 | 2.002 | 0.100 | -0.958 | -0.798 |
|  | 1.090 | 2.271 | 0.733 | 1.245 | 0.922 |
| Craft and related trades | 2.477\*\* | 3.248\*\* | 1.505 | 1.029 | -0.584 |
|  | 1.200 | 1.499 | 0.947 | 0.866 | 2.021 |
| Plant and machine operators | -0.557 | 0.896 | -1.363 | -0.354 | -0.295 |
|  | 1.573 | 1.203 | 0.833 | 0.662 | 0.630 |
| Elementary occupation | -0.663 | 1.144 | -1.606 | -1.513 | -0.601 |
|  | 0.932 | 1.604 | 1.506 | 1.585 | 0.556 |
| Lowest wage quartile | -0.793 | -0.015 | -0.121 | 0.036 | 1.089 |
|  | -1.613 | -1.061 | -0.632 | -0.814 | -0.710 |
| Second wage quartile | 0.0004 | -0.129 | 0.145 | 0.111 | 0.602 |
|  | 0.703 | 0.895 | 0.376 | 0.554 | 0.381 |
| Third wage quartile | -0.460 | -3.745 | 0.152 | 0.127 | -0.552 |
|  | 0.910 | 2.592 | 0.551 | 0.486 | 0.614 |
| Top wage quartile | 0.767 | 2.477\* | -0.173 | -0.218 | -0.951\*\*\* |
|  | 0.873 | 1.297 | 0.254 | 0.501 | 0.343 |
| Age 18-39 | 0.677 | -0.329 | 0.078 | -0.244 | -0.535 |
|  | -0.936 | -0.963 | -0.325 | -0.475 | -0.559 |
| Age 40-59 | -0.213 | 0.498 | -0.079 | 0.184 | 0.234 |
|  | 0.726 | 1.142 | 0.184 | 0.258 | 0.305 |
| Age 60+ | -0.453 | -0.989 | 0.115 | -0.164 | 0.159 |
|  | 3.271 | 4.552 | 0.288 | 0.450 | 0.512 |
| Constant | -0.115 | -1.296 | -0.33 | -0.246 | 0.263 |
|  | 0.677 | 1.724 | 0.235 | 0.271 | 0.210 |
|  | | | | | |
| Observations | 85 | 68 | 252 | 151 | 157 |
|  | | | | | |
| *Note:* | \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 | | | | |

Note: the variables for frequency of use and for training methods differ across the models. In each model the variables refer to the task as indicated by the dependent variable. \*: p<0.1, \*\*: p<0.05, \*\*\*: p<0.01.

Table 3. Models for skill gaps

There are only a few significant relations between occupations and skill gaps. In particular, it seems that craft workers tend to have skill gaps for both working alongside robots and for controlling robots. As craft workers are also more likely than the average worker to control robots as part of their job, this appears unfortunate.

Workers in crafts and related trades are more likely than average to have a skill gap for working alongside robots or for controlling robots but with the exception of managers, no occupational group is less likely than average to have a skill gap for using robots. Workers in occupational groups that are more likely to use robots (plant and machine operators, and elementary occupation – cf. model 1) are just as likely to be adequately or inadequately trained as the average worker.

The weak effects for age and wage indicate that there is no relationship between workers’ skill gaps and their job experience or their position in the organizational hierarchy.

For AI/ML the results show that workers who use the technology daily tend not to have a skill gap. The result cannot determine whether this is because only the most capable employees work regularly with these technologies or because the experience workers gain through regular use of the technology contributes to reducing any skills gap, they may have had.

# 5 Discussion

The analysis shows that there are significant differences between robot technologies and AI/ML technologies. Less than one in ten workers in Denmark use robots weekly and the use of robots varies significantly with the occupation of the worker and with the worker’s position in the organizational hierarchy (as captured by the worker’s wage). However, a quarter of all workers use AI/ML at least weekly and this is independent of job function and hierarchy. Thus, even though robotics has been around for decades it has only diffused to relatively specific occupations, while the more recent AI/ML has rapidly become pervasive across the economic system. In other words, AI/ML has uses throughout the economic system while robots are used more specifically. This supports the argument by Brynjolfsson et al. (2018) that AI may be a new general purpose technology, and it implies that the adoption of AI and ML may pose a broader and more systematic challenge in terms of labor market restructuring and the need for investments in new skills than the use of robots.

Reducing skill gaps is nevertheless important for dissemination and utilization of both robotics and AI/ML technologies. These seems to be quite pervasive among workers regardless of technology. Approximately 50 percent of workers in the TASK survey reports experiences of skill gaps. These are largest in manufacturing and construction and seems unrelated to the type of work organization. We find an interesting inverse relationship between the share that use AI/ML and the share that reports a skill gap. This might indicate a hampering of diffusion of these technologies because of a lack of skills.

Regarding skill acquisition, the data shows that the main mechanism is peer learning, while formal training seems of lesser importance, but it must be emphasized that the data refer only to the main mechanism. The fact that peer learning is most often the main mechanism for skill acquisition does not mean that formal training is not used to support peer learning. Policy aiming to manage the supply of skills mainly work through formal training so the effectiveness of policy for managing skills in the workforce may hinge on the use of formal training for skill acquisition. The importance of formal training is supported by our analysis which shows that in general using formal training as the main mechanism for skill acquisition is associated with fewer skill gaps. There might be important interactions in skill formation between peer learning and formal training, but in any circumstance, we recommend further discussion as to how the educational and vocational systems could play a more pronounced role for skill acquisition in the future.

As mentioned above work organization has no statistically significant relationship with skill gaps, while workers using new technologies are more likely to have Lean work organization. Thus, firms adopting new technologies find ways to cover skill formation regardless of their choice of work organization. Other research has found that work organization along the lines of DL organization makes firms more innovative and workers more satisfied (Lorenz and Holm, this volume), and our results suggest that such work organization can be promoted without compromising skill sufficiency.

The results presented in this paper show that the use of robots is confined to a relatively narrow set of industries and occupational groups in the Danish NSI, while AI and ML are more widely diffused. AI and ML are also more diffused in absolute terms compared to robots. The results indicate that these technologies are impacting firms and workers more pervasively than robotics at the aggregate. Thus, while employees, as represented by unions, have embraced robotics and to some degree facilitated employers’ adoption of robotics for automation, AI and ML have diffused much more widely without such explicit support. While robotics has for decades been a productivity enhancing technology that allows manufacturing firms to remain cost competitive in globalized competition, it remains to be seen whether AI and ML will have the same role over coming decades for more or less all industries and occupations in the economy. Our results show that using AI or ML technologies is strongly associated with Lean work organization, suggesting that adoption of AI or ML is either easier with Lean work organization, or leads to a more Lean form of work organization. However, if Lean facilitates the adoption of AI and ML then Lean work organization should also be associated with less skill gaps, which we do not find. Hence, as Lean is elsewhere found to be associated with less innovation and less job satisfaction compared to specific other forms of work organization, there may be some voluntarism in the way AI and ML are diffused in the Danish national system of innovation so as to foster forms of work organization that tend to enhance innovative performance and to assure a higher quality of working life (Lorenz and Holm, this volume; Nielsen, Holm and Lorenz, this volume).

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1. Postprint, pre-proofs, version for publication in the book “The Danish National System of Innovation in Transition: Globalization, New and Emerging Technologies and Sustainable Development” edited by Christensen, JL., Gregersen, B., Holm, JR. and Lorenz, E. to be published on Routledge. [↑](#footnote-ref-1)
2. Department of Business and Management, Aalborg University. Corresponding author: Jacob R. Holm jrh@business.aau.dk [↑](#footnote-ref-2)
3. TASK was funded partially by the Obel Family Foundation through the ReDy project and partially by the talent program for young researchers at the faculty of social sciences, Aalborg University. [↑](#footnote-ref-3)
4. The analysis based on EWCS for 2015 excluding health and education in Lorenz and Holm (2020) shows a share for the DL forms very close to the estimate based on TASK. [↑](#footnote-ref-4)
5. The TASK survey uses a definition of robots that combines the IFR’s definitions of service robots and industrial robots into one broad definition “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”. [↑](#footnote-ref-5)
6. Effect coding still entails leaving out one category to avoid perfect multicollinearity when estimating but the estimate for this category can be derived from the estimates for the included categories. Alternatively, a second regression can be undertaken leaving out a different category. We report estimates for all categories including the category originally left out. [↑](#footnote-ref-6)
7. See Holm et al. (2017) for an analysis of MNCs in Denmark. [↑](#footnote-ref-7)