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Digital Technologies, Job Quality and Employer-Provided Training

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Abstract

The debate on the impact of digital technologies on the labor market has so far primarily focused on aggregate employment and wage effects. While the impact on the quantity of jobs has been extensively studied, we know relatively little about the impact of digitalisation on the quality of jobs. This study addresses this gap by examining the individual-level relationship between exposure to digital technologies and job quality. Additionally, it explores the mediating role of employer-provided training and personnel management. I use a linked employer-employee survey and administrative data on employees and establishments from Germany which I combine with occupational exposure to basic computer technologies as well as to artificial intelligence. The findings reveal that exposure to advanced digital technologies, such as artificial intelligence and machine learning, is associated with improved working conditions and increased participation in employer-provided training. Conversely, high exposure to basic digital technologies, like computers and computer-controlled machines, correlates with lower job quality and decreased training participation. These effects are more pronounced among male and older employees, underscoring the varied impacts of digital technology exposure across demographic groups.

Keywords: Digitalisation, Artificial Intelligence, Job Quality, Employer-provided Training

1 Introduction

Digitalisation and the adoption of technologies based on artificial intelligence is increasingly affecting the way we work and the changes induced by these technologies are so profound, that many call the phenomenon the Fourth Industrial Revolution. This revolution is built on digital technologies that harness the power of the internet, smart sensors, and advanced microchips, enabling unprecedented interactions between machines and humans that were unimaginable even two decades ago (Brynjolfsson and McAfee, 2014).

Despite their growing importance, the impact of these technologies on labor markets and how their effects compare to previous waves of technological change remain unclear. Much of the existing economic literature has focused on automation and the potential job losses associated with it, with some studies reporting alarming (Frey and Osborne, 2017) or moderately negative (Arntz et al., 2017) employment effects. These negative effects of automation technologies on employment have been documented at the level of local labor markets as well as for individual workers (Acemoglu and Restrepo, 2020; Dauth et al., 2021; Bessen et al., 2019).

While most studies on the labor market effects of digitalisation focus on the quantity of jobs (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos et al., 2014), I investigate the relationship between digital technologies and job quality, which has recently been identified as a key issue by the OECD (2023) and is relatively less studied¹. I focus on working conditions that encompass job content and context as objective components of job quality as main outcomes. Additionally, I investigate subjective components of job quality such as job satisfaction and work-life balance. In contrast to the previous literature that largely centers on the displacement effect of automation and digitalisation (Acemoglu and Restrepo, 2019), I investigate effects on incumbent workers. These workers remain in their jobs, as they are not fully replaced by technology, but still experience significant changes in working conditions.

Digitalisation is important for job quality as the introduction of new digital technologies affects the tasks workers perform in their jobs as well as the organization of production (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019). Automation of repetitive or dangerous tasks can lead to improvements in job quality, for example when machines take over physically demanding activities (Green, 2012; Gunadi and Ryu, 2021; Gihleb et al., 2022). Conversely, digitalisation can have negative effects on job quality by causing stress and automation anxiety, increasing surveillance,

¹See Hauret et al. (2020) for an overview of the literature on digitalisation and job quality.

or diminishing the sense of purpose by automating tasks that employees enjoyed performing (Gerten et al., 2019; Schwabe and Castellacci, 2020; Nazareno and Schiff, 2021; Dengler and Gundert, 2021). The negative effects of technostress are described extensively in the psychological literature (Tarafdar et al., 2007; Ragu-Nathan et al., 2008; Ayyagari et al., 2011; Gerdiken et al., 2021). In a study utilizing individual-level data from Australia, Lordan and Stringer (2022) find a negative association between occupational automation risk and employees' mental health. In contrast, Giuntella et al. (2023) find no significant negative relationship between exposure to artificial intelligence and mental health for a sample of German workers. Job quality is also closely related to subjective well-being which is naturally important for employees. But also employers should be interested in increasing employee well-being, given that a large body of literature documents a positive relationship between subjective well-being and performance (DiMaria et al., 2019; Bryson et al., 2017; Judge et al., 2001; Oswald et al., 2015). However, for firms to fully unlock the productivity potential of new digital technologies, it is important to restructure work processes (Agrawal et al., 2023), which can come with a strain on employees' well-being.

The impact of digital technologies on labor in different tasks also depends on the type of technology. In addition to the direct displacement effect, digital technologies also augment human labor in other tasks, reorganize the set of tasks humans perform on their jobs and change the organization of the production process (see Acemoglu and Restrepo, 2018; Acemoglu and Restrepo, 2019; Autor et al., 2003; Autor and Dorn, 2013; Bessen, 2016; Bloom et al., 2014; Lindbeck and Snower, 2000). In this context, basic digital technologies such as computers and computer-controlled machines mostly automate routine tasks (Autor et al., 2003), which lead to increasing demand for complementary interactive tasks. However, more advanced technologies such as artificial intelligence have the potential to perform much more complex tasks in which humans previously had a comparative advantage (Agrawal et al., 2019 2023). This can extend the replacement effect to more non-routine tasks and further increase augmentation effects for complementary tasks.

As outlined above, digitalisation can potentially have negative effects for incumbent workers that are not fully replaced by technology. When examining the labor market effects of digital technologies, it is therefore crucial to recognize that the relationship between technology and humans is dynamic, as workers and employers adapt to new technologies and the challenges they present. Bartel et al. (2007), for example, show that IT adoption leads to increasing skill requirements as the production process is re-organized. One way of dealing with changes in work processes and the introduction of new technologies is for employers to provide their employees with further training (Haepf, 2021; Lukowski

et al., 2020; Wotschack, 2020). However, employers could also reduce training provision after the introduction of advanced digital technologies as found by Brunello et al. (2023). Therefore, I study whether participation in employer-provided training enhances workers' resilience to workplace changes brought about by digital technologies.

In this study, I investigate how digitalisation affects the quality of jobs. Job quality is a broad concept that includes both more objective as well as more subjective components (Nikolova and Cnossen, 2020). Objective components are mostly determined by employers and include working conditions and contractual agreements. Subjective components can be understood as capturing employees' perceptions and encompass measures of satisfaction, well-being and health (Clark, 2015). In my analysis, I incorporate the employer side by considering establishment characteristics and human resource management practices. This approach allows to assess the effectiveness of management practices in mitigating potential negative effects of digitalisation.

To estimate the effects of digitalisation on job quality, I use a linked employer-employee survey from Germany, combined with administrative data and a set of variables measuring occupational exposure to basic and advanced digital technologies.

The main dataset used is the Linked Personnel Panel (LPP-ADIAB), provided by the Institute for Employment Research of the Federal Employment Agency of Germany ², which covers the years 2012-2018. I use the employee survey to measure job quality and the employer survey for firm characteristics and personnel management practices. Additionally, I obtain information on job characteristics from administrative employment records, including detailed information on employment spells, education, wages and occupations. Each establishment is matched with data from the IAB Establishment Panel, which includes information on size, age, industry, location, and investment decisions, among others.

To measure digitalisation, I use data on occupational exposure to basic and advanced digital technologies. These variables include measures of occupational susceptibility to computerization (Dengler and Matthes, 2018), routine task intensity (RTI) (Mihaylov and Tijdens, 2019) as well as exposure to artificial intelligence (Felten et al., 2019) and machine learning (Brynjolfsson et al., 2018). Each measure is examined separately to determine whether there are differences in their impacts on employees. Measures like RTI and computer technology are frequently used in the literature as proxies for automation, primarily in routine tasks (see Autor et al. (2003) for an early example). In contrast, advanced technologies such as artificial intelligence, are expected to also affect occupations that are

²For a detailed description of the LPP-ADIAB see Broszeit et al. (2017), Kampkötter et al. (2016) and Ruf et al. (2019).

less reliant on routine tasks (Brynjolfsson et al., 2018; Agrawal et al., 2019 2023).

I estimate models at the individual worker level, where the main outcomes are working conditions and participation in employer-provided training. Exposure to digital technologies varies by occupation and employer, as firms decide whether they invest in digital technologies and hence facilitate the adoption. I then estimate ordinary least squares (OLS) and linear probability regressions in models with a rich set of control variables. Exploiting the panel dimension of the establishment data, I use establishment and year fixed effects to control for unobserved time-invariant characteristics of the employer side. Using this approach considerably improves upon simple correlations between occupational technology exposure and employee level outcomes.

I find that high exposure to AI and machine learning is associated with improved working conditions and well-being. Notably, employees in high-exposure occupations experience positive effects, particularly in terms of stress reduction and increased autonomy. In contrast, employees with a high computerization risk experience poorer working conditions. Using a high routine task intensity as a proxy for automation, following Autor et al. (2003), leads to similar results, showing that employees exposed to basic digital technologies such as computers and ICTs experience lower job quality.

Regarding participation in employer-provided training, my findings show that employees in occupations with high AI exposure are more likely to receive training than those in occupations with a high computerization risk or a high share of routine tasks. This contrast presents thought-provoking implications for the ongoing discussion on skill- and routine-biased technological change. The prevailing argument suggests that employees at risk of technological displacement should participate in additional training to improve their skill sets. However, the observed pattern raises questions about whether this approach is effectively addressing the diverse challenges faced by employees in different types of occupations impacted by digitalisation.

This paper makes three important contributions to the existing literature. The first one is to highlight the importance of job quality for incumbent workers in the discourse on the labor market impacts of digitalisation and to provide new empirical evidence for Germany. Understanding how job quality is influenced by digitalisation is essential, given the rapid development of new technologies and the significant adjustments required in the workforce. As most of the previous literature focused on the displacement of human labor, I provide new evidence on the effects of digitalisation on those workers who are exposed to new technologies but remain employed in their occupation. By leveraging the strengths of the data that incorporate administrative employment records, firm characteristics, and survey data from both employer and employee perspectives, this study provides a comprehensive analysis of the

impact of digital technologies on job quality in Germany. The second contribution is to explicitly compare the impact of basic technologies such as computers and ICT to that of artificial intelligence and machine learning. In a task-based approach (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019), different technologies affect different tasks in production, which leads to distinct effects on occupations and workers. While basic digital technologies are mainly automating routine tasks, it has been argued that artificial intelligence also affects non-routine tasks (Agrawal et al., 2019; Brynjolfsson et al., 2018). The third contribution is to provide evidence on the adjustment of firms and employees to digital technologies by incorporating the employer side in the analysis. The main mechanisms I investigate are employer-provided further training and personnel management practices, which have a mediating effect on the consequences of digitalisation.

The remainder of the paper is organized as follows: Section 2 introduces and describes the data used. Section 3 presents the empirical strategy while the corresponding main results are shown in section 4. Additional results are provided in section 5 and a series of robustness checks in section 6. Section 7 discusses the results and finally, section 8 concludes the paper.

2 Data

Studying the impact of digitalisation on job quality at an individual worker level imposes some challenging data requirements. While data on employees alone might be somewhat informative, many effects could potentially be attributed to firm differences. Therefore, data on the employer side is necessary. In this study, I combine three different sources of data that are explained in more detail below. First, a linked employer-employee survey which provides measures of job quality as well as employer characteristics. Next, administrative records provide further objective measures of job quality as well as detailed occupational codes and wage data. Finally, a set of variables measuring occupational exposure to basic and advanced digital technologies is merged to complement the survey and administrative data.

2.1 Linked Personnel Panel

To analyze job quality and training participation of employees, I use the Linked-Personnel Panel (LPP) merged with administrative employment and establishment records of the Federal Institute for Employment Research (IAB). The data cover the years 2012-2018³.

³For a detailed description of the LPP-ADIAB see Broszeit et al. (2017), Kampkötter et al. (2016) and Ruf et al. (2019).

The LPP is a survey based on the IAB Establishment Panel, which is a large panel of approximately 16,000 establishments in Germany. From this panel, a sample of establishments and employees is drawn for the LPP survey. The sample is stratified by broad occupations, five sectors, and four regions, resulting in an average of 875 establishments and 7,000 employees across the five survey waves. Overall, the data is representative of German firms in manufacturing and services with more than 50 employees. Employee attrition is a factor, as they are not necessarily included in all waves of the survey. As such, employees are treated as repeated cross-sections, with only 15% appearing in every wave. In contrast, 85% of establishments are sampled repeatedly, and 43% are included in all waves.

The survey provides me with the primary outcomes job quality, working conditions and employer-provided training. I build an index for working conditions that comprises five items which are each rated on a scale from 1 to 5. The items included are decision autonomy, task variety, time pressure, physical effort and ambient conditions. They are coded such that a higher value implies better working conditions. In addition, the survey includes a rich set of variables on employees' background and personality.

One of the main advantages of the LPP is that it covers both the employee and the employer side. The employer survey focuses on personnel management practices and provides additional information on firm characteristics like size, industry, ownership structure, collective bargaining agreements as well as on job characteristics like performance pay or the possibility to work from home.

The LPP survey is then linked to administrative employment records for each employee, providing detailed information on occupation, wage, age, gender, education, qualification, location, and more. Employer-side information can be supplemented from the Establishment History Panel and the IAB Establishment Panel, which surveys a broad range of topics. Especially relevant for this study are questions about investments in information and communication technologies that are included in the Establishment Panel. I use these questions to construct a variable that measures whether a firm invested in ICT equipment in one of the three years prior to the survey. This allows me to qualify the technology exposure at the employee level, assuming that firms with ICT investments are adopting more digital technologies.

2.2 Measures for digital technology exposure

The digitalisation variables serve as measures for occupational exposure to digital technologies and can be defined in two broad categories. Basic digital technologies refer to information and communication technologies like computers, computer-controlled machines and their applications. Advanced digital

technologies refer to technologies based on artificial intelligence that have the potential to affect a wider range of tasks compared to basic ICT, including decision making (see Agrawal et al. (2019)).

To measure the occupational exposure to basic digital technologies, I use two different measures. The first one is a direct measure for computerization and was developed by Dengler and Matthes (2018). They estimate an automation potential due to computerization for occupations in Germany based on the German database BERUFENET ⁴. This database includes a comprehensive register of tasks and work activities, which are subsequently classified based on their susceptibility to computerization. These tasks are then aggregated at the occupation level. Another approach is to indirectly measure the exposure to computerization and ICT based on the routine task intensity of an occupation, following Autor et al. (2003). To do this, I use a routine task intensity index for European occupations developed by Mihaylov and Tijdens (2019).

To measure the occupational exposure to advanced digital technologies, I use two measures that were developed by Felten et al. (2018) and Brynjolfsson et al. (2018). These capture the exposure to occupations to artificial intelligence and machine learning. The measures share a common approach with the computerization measure of Dengler and Matthes (2018), starting at the task level to identify which tasks can be performed by AI and machine learning. Occupational exposure is then calculated based on the proportion of each task within an occupation ⁵.

Table 1 presents summary statistics for the main outcome and control variables as well as for the digitalisation measures.

⁴The BERUFENET database is a database for occupational tasks and abilities in Germany, similar to the O*NET database in the US.

⁵The measures from Felten et al. and Brynjolfsson et al. are based on US occupational data (O*NET) and are mapped to German occupations using a crosswalk from isco08 to the kldb2010 classification. Similar crosswalks have been used in Goos et al. (2014) and Sorgner (2017)).

Table 1: Summary statistics

	Observations	Mean	Std. Dev.	Min	Max
<u>Outcome variables:</u>					
Working conditions	23,108	17.53	3.26	5	25
Training participation	23,140	0.40	.49	0	1
Job satisfaction	23,145	7.47	1.75	0	10
Health status	23,143	2.34	0.93	1	5
Well-being	23,016	14.39	5.12	5	30
<u>Digitalisation Measures:</u>					
Routine Task Intensity	22,772	.4061	.3648	0	1
Computerization	23,162	.54	.25	0	1
AI Exposure	22,340	.5402	.2646	0	1
Machine Learning Suitability	22,343	.6846	.1394	0	1
<u>Control variables:</u>					
Age	23,167	47.28	10.22	18	76
Male	23,167	0.72	0.44	0	1
Education	23,114	3.41	1.15	1	8
Qualification	23,145	2.47	1.65	1	8
Wage (imputed)	23,106	141.22	88.27	0.42	988.46
Firm size	23,123	3345.89	11605.66	1	65229
Leadership	23,136	0.29	0.45	0	1
Fulltime	23,135	0.86	0.33	0	1

3 Empirical Strategy

The empirical strategy builds on employees’ occupational exposure to digital technologies and the variation in working conditions across employers and time. While the actual usage of digital technologies is not directly observed at the worker level, I assume that high occupational exposure increases the likelihood of technology adoption. This is further enriched by the establishment data. Whether a given technology is adopted also varies by establishments. As a proxy for technology adoption at the establishment level, I use data on investment decisions from the IAB Establishment Panel. Investments in ICTs can be regarded as investments in basic digital technologies, as well as laying the foundation for adopting advanced technologies. Consequently, worker-level exposure is likely to differ between high and low adoption firms, even for workers in the same occupation.

The focus of this study are incumbent workers who continue to work in their job, but experience changes due to a shift in tasks caused by technological advances. I also observe workers who still perform the same tasks on their job but with changing intensities. Therefore, this study is not aimed at estimating replacement effects where workers are displaced from their jobs by new technologies. This

group of workers, whose complete job can be performed by technology, would drop out of my sample and could no longer be observed in the data. For workers remaining in their job, digital technologies can negatively affect working conditions by inducing stress and cognitive overload, leading to reduced subjective well-being and job satisfaction. However, if technology automates dangerous or disliked tasks, the change in job content could result in positive outcomes and increased worker well-being. The net effect is an open question ex-ante.

In this setting, variation comes from employees working in different occupations, with varying technology exposure, as well as from employees working in the same occupation but at different establishments. The advancement of digital technologies opens up new possibilities to structure work processes and the tasks that workers perform at their job are likely to change. While some occupations are naturally more prone to digitalisation than others, technology adoption also depends on the employers. For example, employers decide whether to provide their employees with new hardware or software as well as whether they provide assistance to their employees in adapting to the new technologies.

All outcome variables are measured at the individual worker level. Most of these variables are items from the LPP employee survey, coded from 1 to 5. For the working conditions, I aggregate them to an index ranging from 5 to 25. The training variable is a binary response variable, equal to one if the employee participated in training that year and zero otherwise. Additional outcomes such as job satisfaction, well-being and health status are self-reported survey questions included in the LPP employee part. A more objective measure of health is the number of sick days per year of each employee, which I directly obtain from the social-security records.

Using this set of outcomes and the digitalisation measures, I estimate regression equations of the following form:

$$y_{i,o,t,f} = \beta_0 + \beta_1 \text{digi}_{i,o} + \beta_2 X_{i,o,t,f} + \delta \text{establishment}_f + \gamma \text{year}_t + u_{i,o,t,f} \quad (1)$$

where $y_{i,o,t,f}$ is either working conditions, training participation or one of the additional outcomes of worker i in occupation o , year t and firm f . $\text{digi}_{i,o}$ is one of the four occupation-level digitalisation measures, which are used separately in the regressions. The coefficient of interest is β_1 , which captures the impact of a higher occupational digitalisation exposure on the outcome variable $y_{i,o,t,f}$. $X_{i,o,t,f}$ holds a rich set of control variables such as age, gender, highest qualification, wage and whether they work in a leadership position or full-time. To control for additional employer characteristics that vary over time, I also incorporate establishment size and other firm characteristics as control variables in $X_{i,o,t,f}$. Exploiting the panel dimension of the establishment data, I control for a general time trend in the outcomes by including year fixed effects. Further, I include establishment fixed effects to control for

unobserved firm-specific and time-invariant characteristics. Using establishment fixed effects requires companies to be in the sample for at least two waves of the survey. Since attrition is less problematic for establishments than employees, this requirement is met for around 85% of establishments. For binary outcomes like training participation, I estimate logit and linear probability models with the same set of control variables and fixed effects.

There is a risk of potential endogeneity if the explanatory variables are correlated with the error term. For example, if firms with certain characteristics are more likely to invest in digital technologies and also provide better working conditions, then the estimated effect of digitalisation on working conditions may be biased. Another potential problem is omitted variable bias. Both risks are addressed by including a rich set of control variables, as long as the characteristics are observable. To the extent that characteristics are time-invariant at the firm level or are common shocks, including establishment and year fixed effects helps in increasing the robustness of the results.

Another potential threat to identification is selection bias if firms that are investing into ICT technologies are also the ones with the best working conditions. To investigate this selection, I classify firms into investing and non-investing categories based on information from the Establishment Panel. A firm is considered investing if it has invested in ICT technologies in one of the three years preceding the LPP survey, and non-investing otherwise. I then estimate similar regressions as in equation (1) separately for investing and non-investing firms.

4 Results: Working conditions and training

This section presents the main results obtained from regressions based on equation (1). I investigate the effect of technology exposure on job quality, as measured by the working conditions index, and on participation in employer-provided training.

The results for the working conditions are reported in Table 2. All estimations in columns (1) through (4) consistently incorporate the same control variables and fixed effects as detailed in the table notes. The main finding is the contrast between the negative effect of basic digital technologies and the positive effect of advanced technologies.

As shown in columns (1) and (2), a higher routine task intensity as well as a higher computerization score is negatively related to the working conditions index. The estimated coefficients translate into a decline in the working conditions index of up to 2.4 points and are statistically significant at the 5% (column 1) and 1% (column 2) levels. In contrast, exposure to advanced digital technologies, such as

AI and machine learning, is positively related with the working conditions scale, exhibiting an increase of up to 4.5 points or 1.2 standard deviations, based on the AI exposure measure.

Accounting for the observed control variables and the inclusion of establishment fixed effects, it becomes clear that workers in occupations with higher exposure to basic digital technologies encounter poorer working conditions, while those in occupations with greater exposure to advanced digital technologies experience more favorable working conditions. Other determinants of working conditions include age, qualification, and wage, all of which display a positive association with working conditions.

Table 2: Digitalisation and working conditions

Working conditions index	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	-0.503** (0.225)			
Computerization		-2.422*** (0.267)		
<u>Advanced digital technologies:</u>				
AI Exposure			4.540*** (0.353)	
Machine Learning Suitability				4.244*** (0.417)
<u>Control variables:</u>				
Age	0.011** (0.005)	0.009* (0.004)	0.008** (0.004)	0.009 (0.006)
Male	-0.550*** (0.194)	-0.390** (0.162)	0.128 (0.112)	-0.138 (0.162)
Education	0.222** (0.087)	0.158* (0.084)	0.014 (0.082)	0.160* (0.092)
Qualification	0.178*** (0.043)	0.138*** (0.037)	0.100*** (0.033)	0.176*** (0.039)
Wage	0.006*** (0.001)	0.005*** (0.001)	0.002*** (0.001)	0.007*** (0.001)
Firm size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Leadership	0.539*** (0.079)	0.489*** (0.076)	0.506*** (0.078)	0.603*** (0.077)
Fulltime	-0.470*** (0.144)	-0.457*** (0.150)	-0.270* (0.159)	-0.382*** (0.127)
Management controls	No	No	No	No
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.295	0.310	0.355	0.309
Observations	22554	22934	22119	22127

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Demographic controls include age, gender, education, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, I investigate the relationship between technology exposure and training participation. Table 3 presents the outcomes of linear probability models, estimating the association between exposure to digital technologies and the probability of participating in employer-provided training. Analogous to the working conditions case, the RTI and computerization effects contrast with those of AI and machine learning, as indicated by the negative coefficients in columns (1) and (2) and the positive coefficients in columns (3) and (4).

Employees in occupations with the highest routine task intensity are approximately 9% less likely to participate in training offered by their employer as compared to those with the lowest RTI. A higher computerization risk corresponds to an even more pronounced average decrease in the likelihood of training participation of 22.6%. In turn, higher AI or machine learning exposure increases the likelihood of participating in employer-provided training by about 25% and 10% on average, respectively.

With respect to other factors influencing training participation, it is apparent that older employees are less likely to participate in training, while higher qualification and wages are positively correlated with training participation.

To interpret these results, we can think of a skill-based framework, where high-skilled employees possess a comparative advantage in performing complex tasks that require additional training. Consequently, these employees exhibit a higher propensity to receive training. One explication for the findings could then be that occupations characterized by a high share of routine tasks and high computerization scores are predominantly employing low- and medium-skilled workers, while workers in AI-intensive occupations tend to be more highly skilled.

In contrast to the argument to provide training according to comparative advantages, another argument in the debate on training provision is the upskilling of less skilled employees. This is proposed, for example, as a response to skill shortages. My results show that, in my setting, training initiatives are not specifically aimed at upskilling lower skilled workers, at least not in the context of employer-provided training programs.

Table 3: Digitalisation and training participation

Training participation	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	-0.078** (0.037)			
Computerization		-0.223*** (0.042)		
<u>Advanced digital technologies:</u>				
AI Exposure			0.225*** (0.043)	
Machine Learning Suitability				0.110* (0.060)
<u>Control variables:</u>				
Age	-0.005*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)
Male	-0.023 (0.029)	-0.006 (0.029)	0.013 (0.029)	-0.011 (0.026)
Education	0.032*** (0.008)	0.027*** (0.007)	0.024*** (0.008)	0.031*** (0.007)
Qualification	0.014** (0.007)	0.010* (0.006)	0.009* (0.006)	0.018** (0.007)
Wage	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.001*** (0.000)
Firm size	-0.000 (0.000)	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)
Leadership	0.099*** (0.020)	0.096*** (0.019)	0.100*** (0.020)	0.109*** (0.018)
Fulltime	-0.020 (0.029)	-0.018 (0.030)	-0.010 (0.031)	-0.018 (0.024)
Management controls	No	No	No	No
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.218	0.222	0.228	0.216
Observations	22585	22965	22150	22155

Notes: All models estimated are linear probability models with establishment and year fixed effects included. Training participation is one if the employee participated in training in the respective year, zero otherwise. Demographic controls include age, gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As outlined in the empirical strategy section, the extent to which an employee is exposed to digital technologies does not only depend on the occupation but also on their employer. While individual

technology adoption can not be observed in my data, I use information from the Establishment Panel on firms' ICT investment decisions, which serves as a proxy for establishment level technology adoption. Under the hypothesis that firm level adoption of technologies increases the likelihood that employees work with new technologies, we would expect stronger effects for employees in investing firms in the regression analysis.

Table 4: Digitalisation and working conditions conditional on ICT investments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<u>Basic digital technologies:</u>								
Routine Task Intensity	-0.285 (0.247)	-0.582* (0.302)						
Computerization			-1.843*** (0.464)	-2.658*** (0.294)				
<u>Advanced digital technologies:</u>								
AI Exposure					5.051*** (0.352)	4.365*** (0.426)		
Machine Learning Suitability							4.971*** (0.649)	4.031*** (0.450)
<u>Control variables:</u>								
Age	0.005 (0.007)	0.012* (0.007)	0.005 (0.007)	0.008 (0.006)	0.002 (0.006)	0.008 (0.006)	0.003 (0.007)	0.011 (0.008)
Male	-0.867*** (0.194)	-0.448* (0.253)	-0.728*** (0.177)	-0.285 (0.204)	-0.187 (0.159)	0.189 (0.143)	-0.437*** (0.168)	-0.081 (0.204)
Education	0.231*** (0.078)	0.191* (0.116)	0.200*** (0.077)	0.115 (0.111)	-0.000 (0.068)	-0.004 (0.109)	0.187*** (0.070)	0.136 (0.124)
Qualification	0.089* (0.049)	0.206*** (0.058)	0.061 (0.050)	0.157*** (0.046)	0.031 (0.044)	0.117*** (0.042)	0.092* (0.050)	0.206*** (0.053)
Wage	0.007*** (0.002)	0.007*** (0.001)	0.006*** (0.002)	0.005*** (0.001)	0.001 (0.001)	0.003*** (0.001)	0.008*** (0.002)	0.007*** (0.001)
Firm size	0.000*** (0.000)	-0.000* (0.000)	0.000*** (0.000)	-0.000** (0.000)	0.000*** (0.000)	-0.000 (0.000)	0.000*** (0.000)	-0.000 (0.000)
Leadership	0.855*** (0.137)	0.454*** (0.111)	0.892*** (0.136)	0.394*** (0.092)	0.811*** (0.139)	0.435*** (0.104)	0.847*** (0.129)	0.531*** (0.104)
Fulltime	-0.102 (0.246)	-0.589*** (0.171)	-0.061 (0.228)	-0.566*** (0.161)	0.174 (0.204)	-0.340** (0.168)	-0.037 (0.241)	-0.496*** (0.159)
ICT Investment	No	Yes	No	Yes	No	Yes	No	Yes
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.394	0.284	0.400	0.304	0.454	0.342	0.416	0.296
Observation	4989	14444	5078	14671	4955	14102	4931	14165

Notes: All models estimated are OLS with establishment and year fixed effects included. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 reports estimates of regressing the working condition index on technology exposure at the worker level, conditional on the fact that a firm invests in ICT. I split the sample into two groups: Employees at firms that invest in ICT and those that did not. Columns (1), (3), (5) and (7) run

regressions for employees who work at firms without ICT investments whereas columns (2), (4), (6) and (8) report coefficients for employees that work at investing firms. The negative effects of basic digital technologies on working conditions are more pronounced for investing firms, confirming the hypothesis that ICT investments foster the adoption of new technologies and therefore increase their impacts on employees. For advanced technologies, the impacts stay positive but appear to be smaller in investing than in non-investing firms. This shows that, at least for basic digital technologies, the organization of production plays an important role. Without ICT investments, employees are less exposed to negative consequences of digitalisation. However, the firms are likely to also forego potential productivity gains that are associated with technology investments.

Table 5: Digitalisation and training participation conditional on ICT investments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<u>Basic digital technologies:</u>								
Routine Task Intensity	-0.174*** (0.046)	-0.075** (0.035)						
Computerization			-0.212*** (0.067)	-0.231*** (0.057)				
<u>Advanced digital technologies:</u>								
AI Exposure					0.173*** (0.054)	0.264*** (0.047)		
Machine Learning Suitability							-0.035 (0.095)	0.132** (0.052)
<u>Control variables:</u>								
Age	-0.003*** (0.001)	-0.006*** (0.001)	-0.003*** (0.001)	-0.006*** (0.001)	-0.003*** (0.001)	-0.006*** (0.001)	-0.003*** (0.001)	-0.006*** (0.001)
Male	0.045 (0.037)	-0.022 (0.030)	0.066 (0.042)	-0.005 (0.027)	0.066** (0.031)	0.019 (0.026)	0.053 (0.035)	-0.008 (0.028)
Education	0.032** (0.013)	0.029*** (0.009)	0.032*** (0.012)	0.023** (0.009)	0.029** (0.012)	0.019** (0.009)	0.034*** (0.012)	0.028*** (0.009)
Qualification	-0.015 (0.011)	0.025*** (0.009)	-0.016 (0.011)	0.021*** (0.008)	-0.015 (0.011)	0.019** (0.007)	-0.010 (0.011)	0.027*** (0.009)
Wage	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000** (0.000)	0.000** (0.000)	0.001** (0.000)	0.001*** (0.000)
Firm size	0.000* (0.000)	-0.000 (0.000)	0.000* (0.000)	-0.000* (0.000)	0.000* (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Leadership	0.125*** (0.021)	0.105*** (0.022)	0.125*** (0.020)	0.101*** (0.021)	0.118*** (0.022)	0.106*** (0.023)	0.130*** (0.020)	0.119*** (0.021)
Fulltime	0.029 (0.033)	-0.024 (0.027)	0.031 (0.035)	-0.022 (0.027)	0.031 (0.039)	-0.008 (0.027)	0.021 (0.032)	-0.023 (0.026)
ICT Investment	No	Yes	No	Yes	No	Yes	No	Yes
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.301	0.224	0.296	0.229	0.302	0.237	0.288	0.228
Observations	5002	14465	5091	14692	4968	14123	4943	14184

Notes: All models estimated are OLS with establishment and year fixed effects included. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Regarding training participation, as reported in table 5, the differences between investing and non-investing firms are less pronounced and the previously observed pattern of results persists. The negative effect associated with a high routine task intensity is lower for investing firms whereas the effect associated with a higher computerization risk is basically unchanged. In contrast, exposure to advanced digital technologies has positive effects on training participation in investing firms, compared to non-investing firms. For firms that do not invest in ICT, the effects are smaller, in the case of AI exposure, or even negative in the case of ML exposure.

4.1 Results by age and gender

This section separately investigates the relation between digital technologies, working conditions and training for different age groups and by gender. Age groups are defined as young (18-29), middle-aged (30-49) and older (50 and above). We would expect differential results especially by age, as younger workers are generally perceived to be more flexible and open to learning new skills. There could also exist a difference by gender, if for example women are more flexible in adopting new skills than men, or vice versa.

As shown in table 6, across all age groups exposure to advanced digital technologies is associated with better working conditions. The most pronounced effect is observed among middle-aged workers. Conversely, the negative association between exposure to basic digital technologies and working conditions is primarily driven by older workers, where the effect is both negative and statistically significant, with the estimated coefficients being larger than those for the entire sample. One explanation for this finding could be the hypothesis of technostress, where the introduction of a new technology leads to negative effects on wellbeing of employees. While older employees are more experienced in their job and have more task-specific human capital, they likely are less flexible in adjusting to new technologies and environments as their younger colleagues. The introduction of new technologies and the accompanying reorganization of work processes could then lead to more stress for older workers compared to younger ones.

Indeed, table 6 shows that for younger and middle-aged workers, exposure to basic digital technologies does not appear to be associated with poorer working conditions, as the estimated coefficients do not achieve statistical significance. The only exception is the coefficient on computer substitution potential, which is -2.34 for middle aged workers and significant at the 1% level.

Regarding training participation, younger workers seem to be less impacted by both basic and advanced technologies, as most estimated coefficients depicted in table 7 do not reach statistical signif-

icance. The exception is the machine learning suitability measure, which is associated with increased training participation among younger workers. On the other hand, middle-aged and older workers exposed to basic digital technologies are less likely to participate in training. The effects of advanced digital technologies on these age groups are less clear-cut, as not all coefficients are statistically significant.

Taken together, exposure to advanced digital technologies is linked to better working conditions across all age groups, with the strongest effect on middle-aged workers. In contrast, older workers are primarily affected by the negative association between basic digital technologies and working conditions. Younger workers are less impacted by both basic and advanced technologies in terms of training participation.

Tables 8 and 9 in the appendix report the estimation results of working conditions and training by gender. Female and male workers could differ in their reaction to new technologies, which would lead to gender differences of the effects of digital technologies on job quality even within occupations.

For male employees, basic digital technologies are correlated with poorer working conditions and lower training participation. The coefficients for basic technologies, in particular, are larger than those estimated for the entire worker population. In contrast, the relationship between advanced digital technologies, working conditions, and training is positive, consistent with the results for the full sample.

For female workers, the positive association between advanced digital technologies, working conditions, and training participation remains. However, basic digital technologies no longer show a significant correlation with worse working conditions. Nevertheless, these technologies are still associated with a lower likelihood of training participation for female workers.

In summary, it seems that women are less impacted by the decline in working conditions due to basic digital technologies. However, they still experience adverse effects on their participation in employer-provided training. One potential caveat to this analysis is that my sample includes considerably less female workers than male workers.

4.2 Results by sector

This section explores the relationship between digital technologies, working conditions, and training across distinct broad sectors. The sectors are classified as follows: manufacturing (1); metal, electrical and vehicle construction (2); commerce and transport (3); professional and financial services (4); information and communication, other services (5). By examining sectors individually, this analysis takes into account the varying nature of technology adoption across different sectors. In certain sectors, the

automation component of digital technologies may be more prominent, whereas in others, the complementary component may be dominant. This approach enables a more nuanced understanding of how digital technologies impact working conditions and training participation within the unique contexts of each sector.

Working in occupations with high AI exposure is consistently linked to better working conditions across all sectors, as can be seen in table 10. Nevertheless, the effects of exposure to basic digital technologies can vary depending on the sector in which an employee is working. Specifically, in the manufacturing or metal, electrical, and vehicle construction sectors, high exposure to basic digital technologies is associated with poorer working conditions. Conversely, in ICT and other services, basic digital technologies are associated with improved working conditions. For the remaining sectors, the results are inconclusive as the estimated coefficients lack statistical significance.

Table 11 shows the results of regressions by sector using training participation as outcome. Basic digital technologies are associated with lower training participation in all sectors except for professional and financial services, although with varying degrees of statistical significance. In contrast, the coefficients estimated in sector (4) fail to achieve statistical significance.

The positive association between AI exposure and participation in employer-provided training holds across sectors (1), (2) and (4). In sector (3), the estimated coefficients are not statistically significant. In sector (5), AI exposure is associated with reduced training participation.

4.3 Training and personnel management as mediating factors

This section investigates factors that potentially mediate the negative effects of basic digital technologies on employees or further enhance the positive effects of advanced technologies. While the previous section revealed that digitalisation affects the likelihood of participating in employer-provided training, this section studies whether training participation actually weakens the negative effects observed for basic digital technologies and further increases the positive effects of advanced digital technologies. I also investigate the role of the employer side by analyzing whether specific personnel management practices mediate the impact of digitalisation on working conditions and training. The rationale for this is that employers are ultimately responsible for the introduction of new technologies and can provide employees with assistance to facilitate technology adoption.

4.3.1 Employer provided training

As shown in section 5, digitalisation affects the likelihood of participating in employer provided training. But training itself can also be regarded as a mediating factor on the effect of digitalisation on working conditions. This is the case when training improves the adaption to a new technology and, for example, counteracts technostress. In this section, I present evidence that conditional on participating in employer provided training, the negative effects of basic digital technologies on employees are substantially weaker.

Table 12 shows the results for regressions of working conditions on digitalisation measures for two groups of employees, those who did participate in training and those who did not.

The results show that if employees participate in training, the negative effects on working conditions that were observed before are less pronounced. For advanced technologies, the effects are more similar but also slightly weaker, which indicates that training does not accentuate the positive effects of advanced technologies even more.

For the case of exposure to basic digital technologies, employer-provided training is a valid strategy to soften negative impacts on working conditions. However, when interpreting these results, it needs to be taken into account that selection into training is not random which could partially explain the observed differences in effects such that they are not causally attributed to the training but to unobserved individual characteristics that determine training participation. Further research on the specific type of training, for example if participation is mandatory, and its effects is needed in the future.

4.3.2 HR management

The previous sections showed that job quality, training participation, and other employee-level outcomes are influenced by exposure to digital technologies. However, it is important to consider that the impact of these technologies on employees may also be shaped by their employer’s organizational structure and management approach.

Management is ultimately responsible for making decisions regarding the adoption of new technologies and their integration into work processes. As a result, they play a crucial role in mitigating any potential negative effects of technologies on employees. One example of a management practice that could mitigate the adverse effects of digitalisation on job quality is conducting regular employee interviews and implementing mechanisms to incorporate feedback into future decision-making.

I incorporate these management practices as control variables in the regressions and estimate them

using the same methodology employed for the previous results. If employee interviews, for instance, can alleviate the negative effects of digitalisation on job quality, their inclusion in the regressions should reduce the negative coefficients of basic digital technologies on working conditions.

Incorporating controls for management practices, however, does not result in the elimination of the negative effects of basic digital technologies on working conditions and training participation as shown in tables 13 and 14. Similarly, the positive relationship identified between advanced digital technologies, working conditions, and training remains mostly unaffected by the inclusion of management controls.

5 Additional Results: Subjective well-being and health

In addition to the working conditions index, the concept of job quality also incorporates more subjective measures (Nikolova and Cnossen, 2020). In this context, well-being and job satisfaction are important factors (Clark, 2015). Also, low quality jobs can be associated with worse health outcomes, especially if the work is physically demanding or is conducted in strenuous environmental conditions.

Tables 17 to 20 in the appendix present the results of regressions including further outcome variables related to job quality and individual well-being. These outcomes are job satisfaction, sick days, well-being and work-life balance.

In line with the findings from the previous sections, the impacts of basic and advanced digital technologies on job satisfaction appear to diverge. While statistical significance is not given for all estimates, table 17 illustrates that exposure to artificial intelligence or machine learning is associated with higher job satisfaction. In contrast, basic digital technologies are negatively associated with job satisfaction. On average, employees with high exposure to basic digital technologies or a high proportion of routine tasks report lower job satisfaction.

Table 18 displays estimates related to sick days as a direct measure of an employee’s health status, which is not self-reported but rather obtained from social security records. Again, a similar pattern emerges: basic digital technologies correlate with a higher number of sick days, while increased exposure to advanced digital technologies is associated with a significantly lower number of sick days. The estimated coefficients are statistically significant at conventional levels, except for the routine task intensity measure. This finding further emphasizes the contrasting effects of basic and advanced digital technologies on various aspects of employee well-being.

Lastly, tables 19 and 20 present results on self-reported well-being and work-life balance. These results are less consistent compared to the earlier discussed outcomes. For the well-being measure,

all estimated coefficients do not reach statistical significance at the conventional levels. Considering self-reported work-life balance, exposure to basic digital technologies is negatively associated with work-life balance. Exposure to machine learning also shows a negative relationship with work-life balance, however, the estimated coefficient is small and fails to reach statistical significance. In contrast, AI exposure has a positive and statistically significant association with this aspect of job quality.

In summary, these results support the main findings that exposure to basic digital technologies is related to lower job quality, while advanced digital technologies are connected to higher job quality. Furthermore, these findings extend to areas beyond strictly work-related measures, encompassing health and work-life balance.

6 Robustness Checks

To assess the robustness of the main results, I conduct a series of additional checks. First, I estimate the main regressions for different subsets of my sample. As not all employees are observed in all waves of the survey, the panel is unbalanced. To figure out whether the effects depend on workers dropping out of the sample, I limit the sample to employees and establishments observed in at least two periods. The primary outcomes, working conditions and training, do not change significantly. Next, I further restrict the sample to include only employees observed in all four periods. This sample is significantly smaller, with around 3400 observations. The estimated coefficients for basic digital technologies remain mostly negative but lose statistical significance. In contrast, coefficients for advanced digital technologies continue to be positive and mostly statistically significant, with magnitudes similar to those for the unbalanced panel or full sample. By restricting the sample to cases observed for at least two periods, I can identify employees who change occupations and/or employers during the observed periods. I pinpoint 391 employees who switch occupations, with most switches occurring between occupations and employers. The main coefficients remain statistically significant and similar when excluding job switchers. Coefficients estimated solely for job switchers are insignificant due to the small number of job changes observed in the sample.

The next set of checks includes defining the technology exposure variables as binary rather than continuous variables, thereby creating three distinct variables. The first variable equals one if the employee's occupation falls within the lowest quartile of technology exposure and zero otherwise. The second variable equals one if the occupational exposure is above the median, and the third variable equals one if the exposure falls within the highest quartile. These binary variables help characterize

low and high exposure to the respective technologies.

When estimating regressions with binary explanatory variables and working conditions and training as outcomes, the results largely confirm the initial set of regressions. Being in the bottom quartile of basic technology exposure (i.e., low share of routine tasks and low computerization potential) is positively related to working conditions. Using the above-median definition, coefficients on basic digital technology exposure become negative but do not reach statistical significance. Being in the top quartile of RTI exposure is associated with a negative and statistically significant effect on working conditions, while the coefficient for computerization in the top quartile becomes positive and significant. Being in the bottom quartile of exposure to AI is negatively associated with working conditions, while high exposure to AI, using both the median and top quartile measures, is linked to better working conditions.

7 Discussion

As shown in the previous sections, this study presents new evidence on the impact of the exposure to digital technologies on the job quality of incumbent workers. By focusing on workers who remain employed in their jobs, I explicitly study an aspect of digitalisation that has received comparatively little attention in the literature so far. The focus has long been on the displacement effect of digital technologies and studies such as Frey and Osborne (2017) and Arntz et al. (2017) tried to gauge the amount of jobs lost to automation. If there were full technological replacement of workers, I could not capture it in my sample due to data limitations. However, studying incumbent workers yields insights into workers' adjustments to digitalisation and automation that go beyond the displacement effect.

One effect that usually is difficult to capture is the reinstatement effect (Acemoglu and Restrepo, 2019). This effect includes workers intensifying work in other non-automated tasks or performing entirely new tasks as a response to one of their tasks being fully automated. I measure this as changes in job content. In combination with changes in job context, I can investigate comprehensive changes in job quality.

The most striking finding is the difference in the impacts of basic and advanced digital technologies on working conditions. Occupations with a high exposure to basic digital technologies or a high share of routine tasks consistently are associated with worse working conditions whereas exposure to artificial intelligence or machine learning is associated with better working conditions. One possible explanation for this is that they affect a different set of tasks and differ in their automation intensities. While basic digital technologies such as computers are commonly associated with automating routine

cognitive tasks, more advanced technologies can potentially affect less-routine and more complex tasks. Automating these tasks or complementing humans in performing them can be responsible for the improved working conditions. An alternative explanation could be the organization of production and work in occupations that are heavily exposed to basic vs. advanced digital technologies. In this case, differences in job context can explain most of the difference between the two technology classes.

One more general takeaway from this observed difference in effects is that proxy variables for technological change should not be used interchangeably as they can measure very different things. Especially when using task-based models, we need to be clear about the underlying assumptions of how the specific technology automates, augments or reinstates tasks.

The findings of section 4.3 show that there is considerable scope for employers to influence potential effects of digitalisation on their employees. Employer-provided training plays a key role in mitigating negative effects of basic digital technologies on employees and should be extended also to workers at the lower end of the skill distribution. In contrast, personnel management practices like employee interviews can not completely mitigate negative effects on employees when implemented on their own. Finally, firms' investment decisions are important as they facilitate the adoption of digital technologies. As a policy recommendation, firms should accompany their ICT investments with suitable personnel management and training programs in order to keep negative impacts on the job quality of their employees at a minimum.

Although a causal identification of digital technologies' effects on job quality and training is challenging in this empirical setting, the observed patterns align with previous findings on the labor market impacts of digital technologies. However, it also highlights the need for caution when selecting appropriate proxy variables for measuring digitalisation, as impacts can vary considerably between technologies. An extension of this work could involve an event study examining the introduction of new digital technology in a company and measuring employee-level outcomes in response to the introduction.

8 Conclusion

In this study, I examine the relationship between digital technologies, job quality, and participation in employer-provided training, utilizing occupation-level proxy variables for exposure to digital technologies and linked employer-employee data from Germany. Focusing on employees that do not experience full automation of their jobs, but remain employed as they are exposed to digital technologies, provides new insights for the ongoing debate on the digital transformation and its impacts on job quality.

I distinguish between basic and advanced digital technologies, where basic technologies mainly refer to computers and computer-controlled machines, while advanced technologies pertain to artificial intelligence and machine learning. Adopting a task based approach, the substitution and complementing effects of different technologies at the task level vary considerably.

Basic technologies, targeting mostly routine tasks, show significant automation effects and are linked to poorer working conditions and reduced training participation, particularly affecting older, male workers in manufacturing. Conversely, advanced technologies correlate with improved working conditions and increased training participation. This pattern highlights the contrasting effects of digitalisation on job quality between early digital technologies and the currently emerging artificial intelligence and Industry 4.0 technologies.

The study underscores the important role of employers in mediating the impact of digital technologies on job quality. Firms investing in information and communication technologies (ICTs) exacerbate negative effects of basic digital technologies, emphasizing the significance of firm organization.

However, employers can also mitigate adverse impacts. Employer-provided training and personnel management practices, such as employee interviews, prove effective in reducing negative consequences. Navigating the adoption of new digital technologies poses challenges for both companies and employees, with successful implementation enhancing productivity but potentially altering job content and context, negatively affecting working conditions and job quality.

Acknowledging this dual nature of digitalisation, employers should proactively address negative consequences by providing additional training and embracing employee-centric human resource management strategies. This proactive approach is crucial for ensuring the positive outcomes of digital technology adoption while mitigating potential downsides for employees.

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Table 6: Digitalisation and working conditions - by age groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<u>Basic digital technologies:</u>												
Routine Task Intensity	-0.456 (0.624)	-0.277 (0.303)	-1.059*** (0.314)									
Computerization				-1.764* (0.948)	-2.347*** (0.342)	-2.673*** (0.295)						
<u>Advanced digital technologies:</u>												
AI Exposure							3.006* (1.580)	4.925*** (0.414)	4.136*** (0.303)			
Machine Learning Suitability										4.427*** (1.299)	5.345*** (0.510)	2.374*** (0.813)
<u>Control variables:</u>												
Male	-0.925* (0.471)	-0.266 (0.350)	-0.700*** (0.156)	-0.651 (0.462)	-0.182 (0.307)	-0.440*** (0.155)	-0.093 (0.355)	0.224 (0.216)	0.033 (0.146)	-0.271 (0.461)	0.084 (0.288)	-0.259 (0.174)
Education	0.655*** (0.221)	0.353*** (0.062)	0.013 (0.177)	0.610*** (0.233)	0.278*** (0.064)	-0.044 (0.172)	0.452 (0.316)	0.106** (0.052)	-0.156 (0.174)	0.576*** (0.218)	0.256*** (0.062)	-0.057 (0.199)
Qualification	0.106 (0.119)	0.162** (0.076)	0.165** (0.075)	0.082 (0.109)	0.125* (0.065)	0.129* (0.071)	0.062 (0.103)	0.074 (0.061)	0.114 (0.074)	0.107 (0.108)	0.150** (0.072)	0.184** (0.081)
Wage	0.003 (0.005)	0.007*** (0.001)	0.006*** (0.001)	0.001 (0.005)	0.005*** (0.001)	0.005*** (0.001)	0.001 (0.005)	0.003*** (0.001)	0.003*** (0.001)	0.001 (0.005)	0.007*** (0.001)	0.008*** (0.001)
Firm size	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Leadership	0.456 (0.475)	0.411*** (0.140)	0.669*** (0.121)	0.495 (0.446)	0.342*** (0.132)	0.619*** (0.109)	0.637 (0.451)	0.369*** (0.139)	0.642*** (0.117)	0.672 (0.443)	0.406*** (0.130)	0.777*** (0.135)
Fulltime	-0.069 (0.560)	-0.886*** (0.306)	-0.354** (0.170)	-0.023 (0.542)	-0.799*** (0.299)	-0.410** (0.181)	-0.216 (0.548)	-0.504 (0.320)	-0.269 (0.179)	-0.037 (0.546)	-0.716*** (0.244)	-0.308 (0.197)
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R ²	0.521	0.370	0.352	0.521	0.385	0.366	0.541	0.434	0.394	0.538	0.400	0.349
Observations	1717	9634	11203	1770	9784	11380	1722	9447	10950	1736	9473	10918

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 7: Digitalisation and training participation - by age groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<u>Basic digital technologies:</u>												
Routine Task Intensity	0.102 (0.084)	-0.132*** (0.044)	-0.062* (0.037)									
Computerization				-0.193 (0.151)	-0.229*** (0.061)	-0.217*** (0.059)						
<u>Advanced digital technologies:</u>												
AI Exposure							0.065 (0.273)	0.245*** (0.062)	0.209*** (0.038)			
Machine Learning Suitability										0.640*** (0.222)	-0.031 (0.079)	0.108 (0.118)
<u>Control variables:</u>												
Male	-0.019 (0.069)	0.024 (0.046)	-0.075** (0.031)	-0.025 (0.068)	0.040 (0.043)	-0.055* (0.033)	-0.030 (0.115)	0.057 (0.043)	-0.039 (0.031)	0.035 (0.070)	0.023 (0.040)	-0.048* (0.029)
Education	0.071** (0.029)	0.038*** (0.009)	0.027* (0.015)	0.057* (0.031)	0.030*** (0.009)	0.024 (0.015)	0.059* (0.032)	0.025*** (0.009)	0.025 (0.015)	0.048* (0.028)	0.038*** (0.009)	0.025 (0.016)
Qualification	0.035** (0.014)	0.016 (0.011)	0.004 (0.008)	0.027** (0.013)	0.014 (0.010)	0.000 (0.008)	0.030* (0.016)	0.014 (0.010)	-0.003 (0.007)	0.030** (0.013)	0.023** (0.011)	0.006 (0.009)
Wage	0.001 (0.001)	0.000*** (0.000)	0.000*** (0.000)	0.001 (0.001)	0.000*** (0.000)	0.000** (0.000)	0.001 (0.001)	0.000*** (0.000)	0.000*** (0.000)	0.001 (0.001)	0.001*** (0.000)	0.001*** (0.000)
Firm size	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Leadership	0.163** (0.066)	0.103*** (0.028)	0.086*** (0.022)	0.154** (0.061)	0.099*** (0.026)	0.083*** (0.023)	0.167*** (0.064)	0.103*** (0.029)	0.090*** (0.022)	0.181*** (0.062)	0.114*** (0.026)	0.093*** (0.023)
Fulltime	0.015 (0.094)	-0.008 (0.050)	-0.015 (0.044)	0.048 (0.102)	0.003 (0.046)	-0.021 (0.045)	0.042 (0.102)	0.015 (0.049)	-0.017 (0.043)	0.044 (0.107)	-0.009 (0.046)	-0.029 (0.038)
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R ²	0.459	0.280	0.241	0.452	0.281	0.246	0.451	0.284	0.255	0.463	0.273	0.240
Observations	1719	9643	11223	1772	9793	11400	1724	9457	10969	1737	9481	10937

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 8: Digitalisation and working conditions - by gender

	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male	(7) Female	(8) Male
<u>Basic digital technologies:</u>								
Routine Task Intensity	0.711 (0.538)	-1.140*** (0.269)						
Computerization			-0.771 (0.525)	-2.810*** (0.293)				
<u>Advanced digital technologies:</u>								
AI Exposure					4.418*** (0.734)	4.166*** (0.339)		
Machine Learning Suitability							6.012*** (0.897)	3.121*** (0.579)
<u>Control variables:</u>								
Age	-0.010 (0.008)	0.015*** (0.005)	-0.011 (0.008)	0.011** (0.005)	-0.004 (0.007)	0.010** (0.005)	-0.017** (0.007)	0.014** (0.006)
Education	0.369*** (0.102)	0.103 (0.101)	0.377*** (0.099)	0.024 (0.100)	0.232* (0.122)	-0.061 (0.100)	0.265*** (0.085)	0.076 (0.110)
Qualification	-0.072 (0.067)	0.301*** (0.044)	-0.115** (0.057)	0.263*** (0.040)	-0.095* (0.050)	0.196*** (0.039)	-0.070 (0.058)	0.298*** (0.044)
Wage	0.009*** (0.003)	0.005*** (0.001)	0.007*** (0.002)	0.004*** (0.001)	0.004* (0.002)	0.003*** (0.001)	0.009*** (0.003)	0.006*** (0.001)
Firm size	-0.000*** (0.000)	0.000 (0.000)	-0.000** (0.000)	0.000 (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)	0.000 (0.000)
Leadership	0.287 (0.218)	0.546*** (0.079)	0.225 (0.229)	0.491*** (0.079)	0.258 (0.210)	0.510*** (0.086)	0.279 (0.215)	0.605*** (0.087)
Fulltime	-0.739*** (0.228)	0.050 (0.239)	-0.740*** (0.211)	0.122 (0.239)	-0.500** (0.215)	0.126 (0.233)	-0.696*** (0.226)	0.192 (0.238)
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.399	0.339	0.394	0.355	0.441	0.377	0.425	0.337
Observations	6297	16257	6363	16571	6187	15932	6186	15941

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Demographic controls include age, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Digitalisation and training participation - by gender

	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male	(7) Female	(8) Male
<u>Basic digital technologies:</u>								
Routine Task Intensity	-0.009 (0.037)	-0.127*** (0.033)						
Computerization			-0.195** (0.077)	-0.227*** (0.045)				
<u>Advanced digital technologies:</u>								
AI Exposure					0.194* (0.100)	0.244*** (0.056)		
Machine Learning Suitability							0.019 (0.116)	0.080 (0.077)
<u>Control variables:</u>								
Age	-0.003*** (0.001)	-0.006*** (0.001)	-0.003** (0.001)	-0.006*** (0.001)	-0.003*** (0.001)	-0.006*** (0.001)	-0.003*** (0.001)	-0.005*** (0.001)
Education	0.020 (0.015)	0.030*** (0.009)	0.018 (0.014)	0.025*** (0.009)	0.012 (0.013)	0.024** (0.010)	0.020 (0.015)	0.031*** (0.010)
Qualification	0.016 (0.011)	0.018*** (0.006)	0.011 (0.009)	0.015** (0.006)	0.014 (0.010)	0.011** (0.006)	0.016 (0.011)	0.023*** (0.008)
Wage	0.001*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Firm size	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Leadership	0.087*** (0.028)	0.096*** (0.025)	0.084*** (0.028)	0.094*** (0.023)	0.093*** (0.027)	0.097*** (0.025)	0.091*** (0.027)	0.107*** (0.021)
Fulltime	0.003 (0.029)	0.032 (0.054)	0.008 (0.028)	0.039 (0.052)	0.011 (0.026)	0.040 (0.058)	0.005 (0.029)	0.031 (0.053)
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.394	0.220	0.399	0.221	0.401	0.227	0.392	0.215
Observations	6307	16278	6373	16592	6196	15954	6195	15960

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Demographic controls include age, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Digitalisation and working conditions - by sectors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
<u>Basic digital technologies:</u>																				
Routine Task Intensity	-0.366 (0.246)	-1.043** (0.412)	0.436 (0.540)	0.958** (0.450)	1.160** (0.522)	-2.379*** (0.306)	-3.170*** (0.362)	-0.293 (0.806)	0.544 (0.953)	1.878** (0.730)										
<u>Computerization</u>																				
Advanced digital technologies:																				
AI Exposure											4.390*** (0.931)	4.193*** (0.464)	5.224*** (0.484)	3.771*** (0.933)	4.709*** (1.277)	5.811*** (0.640)	2.939*** (0.504)	4.462*** (1.549)	4.555*** (1.034)	4.707*** (1.241)
<u>Machine Learning Suitability</u>																				
<u>Control variables:</u>																				
Age	0.010* (0.006)	0.026*** (0.007)	-0.017 (0.012)	-0.004 (0.007)	-0.006 (0.011)	0.007 (0.005)	0.020*** (0.006)	-0.018 (0.012)	-0.006 (0.007)	-0.004 (0.012)	0.003 (0.006)	0.021*** (0.006)	-0.013 (0.012)	-0.006 (0.007)	-0.013 (0.011)	0.006 (0.006)	0.025*** (0.008)	-0.020* (0.012)	-0.005 (0.007)	-0.005 (0.011)
Male	-0.815*** (0.262)	-0.468 (0.438)	-0.617* (0.318)	0.175 (0.238)	-0.086 (0.313)	-0.635** (0.254)	-0.217 (0.311)	-0.652** (0.310)	0.109 (0.234)	-0.163 (0.312)	0.089 (0.200)	0.122 (0.230)	-0.012 (0.301)	0.168 (0.208)	0.184 (0.309)	-0.277 (0.289)	-0.121 (0.336)	-0.194 (0.308)	0.294 (0.211)	0.140 (0.332)
Education	0.340*** (0.070)	0.171* (0.097)	0.249*** (0.098)	0.183 (0.123)	0.037 (0.141)	0.293*** (0.061)	0.063 (0.096)	0.243** (0.097)	0.191 (0.127)	0.059 (0.144)	0.149** (0.063)	-0.008 (0.093)	0.017 (0.100)	0.074 (0.097)	-0.273* (0.142)	0.269*** (0.063)	0.149 (0.102)	0.175* (0.092)	0.176 (0.122)	-0.002 (0.138)
Qualification	0.108* (0.060)	0.292*** (0.073)	0.033 (0.073)	0.025 (0.056)	-0.012 (0.097)	0.060 (0.059)	0.231*** (0.057)	0.030 (0.074)	-0.003 (0.056)	0.003 (0.085)	0.073* (0.043)	0.162*** (0.061)	0.001 (0.072)	-0.014 (0.058)	-0.026 (0.092)	0.137*** (0.058)	0.282*** (0.069)	0.033 (0.082)	0.015 (0.058)	-0.015 (0.087)
Wage	0.006*** (0.001)	0.006*** (0.001)	0.015*** (0.004)	0.003* (0.002)	0.005*** (0.002)	0.004*** (0.001)	0.005*** (0.001)	0.014*** (0.004)	0.002 (0.001)	0.005*** (0.002)	0.002 (0.001)	0.003*** (0.001)	0.009*** (0.003)	0.000 (0.001)	0.002 (0.002)	0.006*** (0.001)	0.007*** (0.001)	0.014*** (0.001)	0.002 (0.002)	0.004*** (0.002)
Firm size	-0.000 (0.000)	-0.000 (0.000)	-0.001 (0.001)	-0.000 (0.000)	0.001 (0.001)	-0.000 (0.000)	-0.000 (0.000)	-0.001 (0.001)	-0.000 (0.000)	0.001 (0.001)	-0.000*** (0.000)	-0.000 (0.000)	-0.001* (0.001)	-0.000 (0.000)	0.001 (0.001)	0.000 (0.000)	-0.000 (0.000)	-0.001** (0.001)	-0.000 (0.001)	0.001 (0.001)
Leadership	0.372** (0.157)	0.555*** (0.115)	0.548** (0.253)	0.846*** (0.232)	0.694** (0.316)	0.370** (0.145)	0.481*** (0.099)	0.547** (0.251)	0.882*** (0.235)	0.690** (0.310)	0.248** (0.123)	0.641*** (0.101)	0.359* (0.203)	0.806*** (0.261)	0.579* (0.330)	0.431*** (0.141)	0.679*** (0.111)	0.452* (0.246)	0.846*** (0.241)	0.670** (0.328)
Fulltime	-0.300 (0.227)	-0.955*** (0.305)	0.141 (0.434)	-0.073 (0.202)	-0.166 (0.347)	-0.269 (0.270)	-0.791*** (0.242)	0.138 (0.434)	-0.065 (0.204)	-0.196 (0.345)	-0.142 (0.292)	-0.471* (0.258)	0.120 (0.402)	-0.006 (0.214)	-0.009 (0.391)	-0.041 (0.211)	-0.855*** (0.261)	0.095 (0.416)	-0.093 (0.203)	-0.153 (0.369)
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R ²	0.320	0.269	0.335	0.409	0.374	0.342	0.294	0.334	0.403	0.376	0.378	0.320	0.410	0.438	0.420	0.349	0.268	0.357	0.418	0.388
Observations	5515	7483	1889	2272	1315	5627	7653	1891	2292	1317	5462	7429	1854	2198	1170	5379	7421	1840	2239	1267

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 11: Digitalisation and training participation - by sectors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
<u>Basic digital technologies:</u>																				
Routine Task Intensity	-0.070 (0.044)	-0.113*** (0.043)	-0.120** (0.052)	0.053 (0.050)	-0.116* (0.064)															
Computerization						-0.185*** (0.052)	-0.275*** (0.072)	-0.096 (0.102)	0.073 (0.091)	-0.252** (0.127)										
<u>Advanced digital technologies:</u>																				
AI Exposure											0.213*** (0.044)	0.308*** (0.055)	0.040 (0.094)	0.210** (0.091)	-0.096 (0.098)	0.230*** (0.079)	0.098 (0.069)	-0.179 (0.119)	0.049 (0.165)	-0.429*** (0.148)
<u>Machine Learning Suitability</u>																				
<u>Control variables:</u>																				
Age	-0.006*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)	-0.002 (0.002)	-0.003 (0.003)	-0.006*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)	-0.002 (0.002)	-0.003 (0.003)	-0.007*** (0.002)	-0.006*** (0.001)	-0.004*** (0.001)	-0.002 (0.002)	-0.002 (0.003)	-0.007*** (0.002)	-0.005*** (0.001)	-0.004*** (0.001)	-0.002 (0.002)	-0.003 (0.003)
Male	-0.076*** (0.026)	0.034 (0.049)	-0.012 (0.047)	0.027 (0.040)	-0.092** (0.042)	-0.066** (0.026)	0.057 (0.044)	-0.006 (0.045)	0.021 (0.040)	-0.081** (0.039)	-0.025 (0.023)	0.077* (0.041)	-0.012 (0.040)	0.022 (0.037)	-0.100** (0.039)	-0.042* (0.023)	0.044 (0.044)	-0.026 (0.047)	0.027 (0.039)	-0.104** (0.040)
Education	0.030** (0.014)	0.033*** (0.010)	0.039*** (0.012)	0.017 (0.012)	0.010 (0.017)	0.027** (0.013)	0.025** (0.010)	0.038*** (0.012)	0.018 (0.014)	0.006 (0.017)	0.022 (0.014)	0.023** (0.010)	0.037*** (0.012)	0.014 (0.013)	0.019 (0.019)	0.029** (0.013)	0.033*** (0.013)	0.043*** (0.010)	0.017 (0.017)	0.015 (0.017)
Qualification	-0.003 (0.007)	0.032** (0.014)	-0.010 (0.008)	0.015 (0.010)	0.011 (0.013)	-0.006 (0.008)	0.026** (0.012)	-0.010 (0.008)	0.014 (0.010)	0.007 (0.012)	-0.004 (0.008)	0.020* (0.012)	-0.010 (0.009)	0.013 (0.010)	0.014 (0.014)	-0.001 (0.008)	0.035** (0.014)	-0.009 (0.009)	0.013 (0.012)	0.010 (0.012)
Wage	0.000*** (0.000)	0.000** (0.000)	0.001 (0.000)	0.001 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000* (0.000)	0.001 (0.001)	0.001 (0.000)	0.000 (0.000)	0.000** (0.000)	0.000 (0.000)	0.001** (0.000)	0.001* (0.000)	0.001** (0.000)	0.001*** (0.000)	0.001** (0.000)	0.001 (0.001)	0.001* (0.000)	0.001* (0.000)
Firm size	-0.000*** (0.000)	-0.000 (0.000)	-0.000* (0.000)	0.000* (0.000)	0.000* (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000* (0.000)	0.000* (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000* (0.000)	0.000* (0.000)	0.000 (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000** (0.000)	0.000 (0.000)	0.000 (0.000)
Leadership	0.093*** (0.030)	0.100*** (0.028)	0.105*** (0.036)	0.154*** (0.042)	0.141*** (0.041)	0.096*** (0.029)	0.093*** (0.027)	0.107*** (0.037)	0.156*** (0.042)	0.146*** (0.042)	0.088*** (0.030)	0.108*** (0.027)	0.102*** (0.038)	0.143*** (0.043)	0.163*** (0.044)	0.108*** (0.023)	0.116*** (0.023)	0.106*** (0.036)	0.158*** (0.042)	0.141*** (0.041)
Fulltime	-0.084*** (0.030)	-0.050 (0.032)	0.095** (0.042)	0.063* (0.034)	0.048 (0.038)	-0.092*** (0.031)	-0.039 (0.050)	0.094** (0.042)	0.060* (0.033)	0.056 (0.037)	-0.083*** (0.030)	-0.012 (0.055)	0.066** (0.041)	0.050 (0.036)	0.051 (0.038)	-0.074*** (0.028)	-0.054 (0.051)	0.098** (0.044)	0.053 (0.033)	0.050 (0.037)
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R ²	0.291	0.184	0.286	0.292	0.280	0.294	0.189	0.283	0.293	0.284	0.299	0.196	0.290	0.303	0.303	0.291	0.183	0.282	0.293	0.290
Observations	5527	7501	1891	2275	1316	5639	7671	1893	2295	1318	5475	7447	1856	2200	1171	5390	7438	1842	2241	1268

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthies uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 12: Digitalisation and working conditions - conditional on training

	(1) No Training	(2) Training	(3) No training	(4) Training	(5) No training	(6) Training	(7) No training	(8) Training
<u>Basic digital technologies:</u>								
Routine Task Intensity	-0.653** (0.276)	-0.073 (0.239)						
Computerization			-2.747*** (0.329)	-1.725*** (0.282)				
<u>Advanced digital technologies:</u>								
AI Exposure					4.651*** (0.358)	3.729*** (0.640)		
Machine Learning Suitability							4.112*** (0.541)	4.013*** (0.803)
<u>Control variables:</u>								
Age	0.010* (0.006)	0.021*** (0.005)	0.007 (0.006)	0.019*** (0.005)	0.008 (0.005)	0.016*** (0.005)	0.008 (0.006)	0.019*** (0.007)
Male	-0.721*** (0.208)	-0.252 (0.192)	-0.546*** (0.170)	-0.175 (0.171)	-0.096 (0.119)	0.333** (0.156)	-0.372** (0.178)	0.124 (0.183)
Education	0.139 (0.127)	0.265*** (0.070)	0.082 (0.127)	0.203*** (0.071)	-0.078 (0.121)	0.102 (0.082)	0.079 (0.135)	0.197*** (0.063)
Qualification	0.125*** (0.041)	0.217*** (0.053)	0.089** (0.037)	0.185*** (0.050)	0.062* (0.036)	0.143*** (0.053)	0.128*** (0.039)	0.204*** (0.046)
Wage	0.009*** (0.001)	0.003*** (0.001)	0.008*** (0.001)	0.002** (0.001)	0.005*** (0.001)	0.000 (0.001)	0.010*** (0.001)	0.003*** (0.001)
Firm size	-0.000*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)
Leadership	0.584*** (0.090)	0.353*** (0.127)	0.516*** (0.092)	0.312** (0.125)	0.520*** (0.098)	0.371** (0.148)	0.662*** (0.094)	0.405*** (0.131)
Fulltime	-0.521** (0.223)	-0.446** (0.175)	-0.450** (0.205)	-0.496** (0.213)	-0.118 (0.193)	-0.479** (0.233)	-0.451** (0.205)	-0.372*** (0.138)
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.320	0.331	0.332	0.345	0.371	0.381	0.329	0.348
Observations	13373	9168	13656	9265	13239	8868	13249	8865

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Digitalisation and working conditions - management controls

	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	-0.409** (0.203)			
Computerization		-2.294*** (0.249)		
<u>Advanced digital technologies:</u>				
AI Exposure			4.264*** (0.348)	
Machine Learning Suitability				4.008*** (0.437)
<u>Control variables:</u>				
Age	0.017*** (0.005)	0.014*** (0.004)	0.014*** (0.004)	0.015*** (0.006)
Male	-0.506*** (0.168)	-0.366*** (0.139)	0.110 (0.097)	-0.131 (0.141)
Education	0.204** (0.089)	0.144* (0.086)	0.013 (0.083)	0.143 (0.093)
Qualification	0.169*** (0.039)	0.129*** (0.034)	0.098*** (0.031)	0.163*** (0.036)
Wage	0.005*** (0.001)	0.004*** (0.001)	0.002*** (0.001)	0.006*** (0.001)
Firm size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Leadership	0.451*** (0.084)	0.396*** (0.081)	0.428*** (0.083)	0.493*** (0.078)
Fulltime	-0.443*** (0.137)	-0.426*** (0.152)	-0.258 (0.166)	-0.347*** (0.111)
Employee interviews	1.018*** (0.106)	0.984*** (0.091)	0.762*** (0.098)	1.018*** (0.098)
Performance pay	0.042 (0.082)	0.048 (0.083)	0.064 (0.080)	0.068 (0.078)
Teamwork	-0.443*** (0.051)	-0.462*** (0.047)	-0.457*** (0.039)	-0.466*** (0.048)
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.324	0.340	0.379	0.340
Observations	22479	22859	22044	22054

Notes: All models estimated are OLS with establishment and year fixed effects included. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Digitalisation and training participation - management controls

	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	-0.068*			
	(0.035)			
Computerization		-0.203***		
		(0.043)		
<u>Advanced digital technologies:</u>				
AI Exposure			0.179***	
			(0.041)	
Machine Learning Suitability				0.068
				(0.063)
<u>Control variables:</u>				
Age	-0.005***	-0.005***	-0.005***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Male	-0.017	-0.002	0.011	-0.010
	(0.028)	(0.028)	(0.029)	(0.025)
Education	0.029***	0.024***	0.023***	0.028***
	(0.008)	(0.007)	(0.008)	(0.007)
Qualification	0.012*	0.009	0.009	0.015**
	(0.006)	(0.006)	(0.006)	(0.007)
Wage	0.000***	0.000***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm size	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Leadership	0.086***	0.083***	0.088***	0.093***
	(0.020)	(0.019)	(0.020)	(0.018)
Fulltime	-0.019	-0.017	-0.012	-0.016
	(0.028)	(0.030)	(0.031)	(0.024)
Employee interviews	0.151***	0.148***	0.136***	0.159***
	(0.015)	(0.015)	(0.014)	(0.014)
Performance pay	0.024**	0.025**	0.027**	0.028**
	(0.012)	(0.012)	(0.012)	(0.013)
Teamwork	-0.016*	-0.017*	-0.016*	-0.015*
	(0.010)	(0.010)	(0.010)	(0.009)
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.233	0.238	0.240	0.233
Observations	22508	22888	22074	22082

Notes: All models estimated are OLS with establishment and year fixed effects included. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Digitalisation and job content

	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	-0.455*** (0.063)			
Computerization		-0.555*** (0.092)		
<u>Advanced digital technologies:</u>				
AI Exposure			0.433*** (0.162)	
Machine Learning Suitability				-0.033 (0.229)
<u>Control variables:</u>				
Age	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)
Male	0.062 (0.049)	0.143*** (0.048)	0.190*** (0.053)	0.107** (0.050)
Education	-0.031 (0.020)	-0.041** (0.019)	-0.046* (0.024)	-0.025 (0.024)
Qualification	0.026* (0.015)	0.021 (0.015)	0.023* (0.014)	0.027* (0.015)
Wage	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.004*** (0.000)
Firm size	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.159	0.154	0.155	0.152
Observations	22615	22998	22182	22189

Notes: All models estimated are OLS with establishment and year fixed effects included. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Digitalisation and job context

	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	-0.279 (0.195)			
Computerization		-2.376*** (0.257)		
<u>Advanced digital technologies:</u>				
AI Exposure			4.742*** (0.286)	
Machine Learning Suitability				4.729*** (0.368)
<u>Control variables:</u>				
Age	0.011*** (0.004)	0.008** (0.003)	0.007*** (0.002)	0.008** (0.004)
Male	-0.753*** (0.185)	-0.631*** (0.157)	-0.024 (0.127)	-0.283* (0.166)
Education	0.354*** (0.067)	0.286*** (0.062)	0.129** (0.056)	0.279*** (0.072)
Qualification	0.197*** (0.047)	0.154*** (0.036)	0.114*** (0.033)	0.192*** (0.042)
Wage	0.006*** (0.001)	0.004*** (0.001)	0.002*** (0.000)	0.006*** (0.001)
Firm size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.396	0.421	0.502	0.427
Observations	22609	22992	22175	22181

Notes: All models estimated are OLS with establishment and year fixed effects included. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17: Digitalisation and job satisfaction

Job Satisfaction	(1)	(2)	(4)	(5)
<u>Basic digital technologies:</u>				
Routine Task Intensity	-0.123 (0.084)			
Computerization		-0.215 (0.153)		
<u>Advanced digital technologies:</u>				
AI Exposure			0.330** (0.141)	
Machine Learning Suitability				0.147 (0.194)
<u>Control variables:</u>				
Age	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.005* (0.003)
Male	-0.049 (0.047)	-0.010 (0.048)	0.028 (0.047)	-0.031 (0.044)
Education	-0.101** (0.040)	-0.103** (0.041)	-0.114*** (0.043)	-0.097** (0.039)
Qualification	-0.000 (0.021)	-0.002 (0.020)	-0.006 (0.021)	0.009 (0.019)
Wage	0.001** (0.000)	0.001* (0.001)	0.001* (0.000)	0.001** (0.001)
Firm size	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Leadership	0.236*** (0.031)	0.236*** (0.030)	0.244*** (0.033)	0.264*** (0.034)
Fulltime	0.133 (0.158)	0.121 (0.155)	0.126 (0.157)	0.104 (0.146)
Management controls	No	No	No	No
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.143	0.141	0.143	0.145
Observations	22590	22970	22155	22160

Notes: All models estimated are OLS with year and establishment fixed effects added. Demographic controls include age, gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 18: Digitalisation and sick days

Sick days	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	3.185 (2.002)			
Computerization		6.366*** (2.307)		
<u>Advanced digital technologies:</u>				
AI Exposure			-11.333*** (2.344)	
Machine Learning Suitability				-5.734*** (1.947)
<u>Control variables:</u>				
Age	0.297*** (0.047)	0.300*** (0.049)	0.301*** (0.047)	0.298*** (0.050)
Male	-0.758 (1.089)	-1.332 (0.859)	-2.516*** (0.770)	-1.369 (0.971)
Education	-0.454 (1.194)	-0.257 (1.218)	0.175 (1.258)	-0.225 (1.207)
Qualification	0.025 (0.502)	0.060 (0.485)	0.120 (0.472)	-0.099 (0.532)
Wage	-0.036*** (0.008)	-0.035*** (0.008)	-0.030*** (0.008)	-0.044*** (0.010)
Firm size	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Leadership	-1.869*** (0.498)	-1.804*** (0.516)	-1.831*** (0.493)	-1.768*** (0.539)
Fulltime	3.684*** (1.373)	3.747*** (1.340)	3.115** (1.311)	3.722*** (1.402)
Management controls	No	No	No	No
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.181	0.180	0.189	0.181
Observations	15945	16214	15629	15689

Notes: All models estimated are OLS with year and establishment fixed effects added. Demographic controls include age, gender, qualification, wage and establishment size. Region is East or West Germany. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 19: Digitalisation and well-being

Well-being	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	0.302 (0.314)			
Computerization		0.477 (0.407)		
<u>Advanced digital technologies:</u>				
AI Exposure			-0.098 (0.379)	
Machine Learning Suitability				-0.073 (0.493)
<u>Control variables:</u>				
Age	-0.025** (0.010)	-0.024** (0.010)	-0.025** (0.010)	-0.024*** (0.008)
Male	-0.697** (0.274)	-0.751*** (0.290)	-0.769*** (0.288)	-0.700*** (0.269)
Education	0.250*** (0.085)	0.269*** (0.089)	0.256*** (0.089)	0.250*** (0.081)
Qualification	0.015 (0.043)	0.013 (0.041)	0.001 (0.041)	0.020 (0.050)
Wage	-0.002* (0.001)	-0.002* (0.001)	-0.003** (0.001)	-0.002** (0.001)
Firm size	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Leadership	-0.952*** (0.139)	-0.940*** (0.127)	-0.936*** (0.130)	-0.952*** (0.133)
Fulltime	0.134 (0.205)	0.152 (0.207)	0.161 (0.212)	0.239 (0.268)
Management controls	No	No	No	No
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.127	0.124	0.126	0.124
Observations	22473	22849	22035	22044

Notes: All models estimated are OLS with year and establishment fixed effects added. Demographic controls include age, gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 20: Digitalisation and work-life balance

Work-life balance	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	-0.204** (0.087)			
Computerization		-0.434** (0.169)		
<u>Advanced digital technologies:</u>				
AI Exposure			0.330** (0.153)	
Machine Learning Suitability				-0.128 (0.163)
<u>Control variables:</u>				
Age	0.001 (0.004)	0.000 (0.003)	0.001 (0.004)	0.000 (0.004)
Male	-0.059 (0.068)	-0.029 (0.071)	0.008 (0.073)	-0.032 (0.073)
Education	-0.013 (0.029)	-0.026 (0.030)	-0.029 (0.033)	-0.011 (0.032)
Qualification	0.033* (0.019)	0.027 (0.020)	0.028 (0.019)	0.035* (0.018)
Wage	0.001** (0.001)	0.001** (0.001)	0.001** (0.001)	0.001*** (0.000)
Firm size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)
Leadership	0.091 (0.062)	0.089 (0.060)	0.104* (0.062)	0.134** (0.056)
Fulltime	-0.177 (0.108)	-0.172 (0.111)	-0.152 (0.117)	-0.176 (0.112)
Management controls	No	No	No	No
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.165	0.166	0.166	0.159
Observations	10408	10578	10143	10205

Notes: All models estimated are OLS with year and establishment fixed effects added. Demographic controls include age, gender and wage. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 21: R1: Working conditions - Employees in minimum two waves

Working conditions index	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	-0.467* (0.272)			
Computerization		-2.386*** (0.341)		
<u>Advanced digital technologies:</u>				
AI Exposure			4.513*** (0.448)	
Machine Learning Suitability				4.315*** (0.523)
<u>Control variables:</u>				
Age	0.014** (0.007)	0.011* (0.006)	0.011** (0.005)	0.011 (0.008)
Male	-0.370 (0.281)	-0.247 (0.242)	0.342* (0.182)	0.065 (0.253)
Education	0.185 (0.131)	0.108 (0.126)	-0.035 (0.118)	0.090 (0.141)
Qualification	0.261*** (0.066)	0.228*** (0.061)	0.172*** (0.052)	0.261*** (0.062)
Wage	0.005*** (0.001)	0.004*** (0.001)	0.002*** (0.001)	0.006*** (0.001)
Firm size	0.000* (0.000)	0.000 (0.000)	0.000** (0.000)	0.000* (0.000)
Leadership	0.478*** (0.106)	0.410*** (0.101)	0.452*** (0.111)	0.543*** (0.108)
Fulltime	-0.607*** (0.203)	-0.614*** (0.216)	-0.392** (0.191)	-0.522*** (0.176)
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.333	0.348	0.391	0.347
Observations	14730	14957	14413	14365

Notes: All models estimated are OLS with establishment and year fixed effects included. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 22: R1: Training participation - Employees in minimum two waves

Training participation				
	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	-0.071 (0.053)			
Computerization		-0.254*** (0.053)		
<u>Advanced digital technologies:</u>				
AI Exposure			0.229*** (0.061)	
Machine Learning Suitability				0.201** (0.085)
<u>Control variables:</u>				
Age	-0.006*** (0.001)	-0.007*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)
Male	-0.013 (0.048)	0.004 (0.046)	0.026 (0.051)	0.003 (0.043)
Education	0.030** (0.012)	0.021* (0.012)	0.019 (0.013)	0.024** (0.012)
Qualification	0.012 (0.009)	0.009 (0.007)	0.008 (0.007)	0.019** (0.009)
Wage	0.001*** (0.000)	0.000** (0.000)	0.000** (0.000)	0.001*** (0.000)
Firm size	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Leadership	0.094*** (0.028)	0.089*** (0.027)	0.098*** (0.029)	0.105*** (0.025)
Fulltime	-0.040 (0.030)	-0.043 (0.033)	-0.033 (0.033)	-0.037 (0.025)
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.221	0.229	0.230	0.222
Observations	14747	14974	14431	14382

Notes: All models estimated are OLS with establishment and year fixed effects included. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 23: R2: Working conditions - Employees in four waves

Working conditions index	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	0.268 (0.574)			
Computerization		-2.079*** (0.582)		
<u>Advanced digital technologies:</u>				
AI Exposure			4.565*** (0.942)	
Machine Learning Suitability				3.832*** (1.267)
<u>Control variables:</u>				
Age	0.048*** (0.016)	0.042*** (0.016)	0.051*** (0.015)	0.054*** (0.016)
Male	1.430 (0.981)	1.323 (0.965)	1.740* (0.947)	1.641* (0.963)
Education	0.385** (0.185)	0.325* (0.189)	0.039 (0.150)	0.245 (0.187)
Qualification	0.269* (0.158)	0.212 (0.140)	0.211 (0.139)	0.240 (0.155)
Wage	0.003** (0.002)	0.002 (0.002)	0.000 (0.001)	0.003 (0.002)
Firm size	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Leadership	0.145 (0.241)	0.022 (0.235)	0.003 (0.214)	0.214 (0.261)
Fulltime	-0.826 (0.529)	-0.843 (0.589)	-0.563 (0.555)	-0.751 (0.486)
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.509	0.518	0.546	0.513
Observations	3412	3445	3292	3279

Notes: All models estimated are OLS with establishment and year fixed effects included. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 24: R2: Training participation - Employees in four waves

Training participation	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
Routine Task Intensity	-0.080 (0.068)			
Computerization		-0.255** (0.108)		
<u>Advanced digital technologies:</u>				
AI Exposure			0.319*** (0.096)	
Machine Learning Suitability				0.004 (0.142)
<u>Control variables:</u>				
Age	-0.005** (0.003)	-0.006** (0.003)	-0.007** (0.003)	-0.004 (0.003)
Male	0.026 (0.057)	0.024 (0.055)	0.043 (0.055)	0.030 (0.051)
Education	0.018 (0.022)	0.010 (0.022)	-0.007 (0.023)	0.018 (0.020)
Qualification	0.015 (0.015)	0.011 (0.014)	0.009 (0.015)	0.021 (0.016)
Wage	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Firm size	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Leadership	0.064 (0.041)	0.056 (0.044)	0.078** (0.039)	0.088* (0.049)
Fulltime	0.026 (0.047)	0.030 (0.046)	0.056 (0.046)	0.023 (0.046)
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.301	0.305	0.308	0.308
Observations	3419	3452	3300	3286

Notes: All models estimated are OLS with establishment and year fixed effects included. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 25: R3: Working conditions - Exposure above median

Working conditions index	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
RTI >50pct	-0.192 (0.142)			
Computerization >50pct		-1.220*** (0.114)		
<u>Advanced digital technologies:</u>				
AI Exposure >50pct			2.085*** (0.201)	
ML Suitability >50pct				0.803*** (0.133)
<u>Control variables:</u>				
Age	0.011** (0.005)	0.009** (0.004)	0.010** (0.005)	0.012** (0.005)
Male	-0.504*** (0.187)	-0.353** (0.162)	-0.026 (0.111)	-0.286* (0.156)
Education	0.234*** (0.086)	0.167** (0.084)	0.081 (0.081)	0.181** (0.088)
Qualification	0.182*** (0.042)	0.136*** (0.035)	0.106*** (0.037)	0.185*** (0.040)
Wage	0.007*** (0.001)	0.005*** (0.001)	0.004*** (0.001)	0.006*** (0.001)
Firm size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Leadership	0.576*** (0.081)	0.490*** (0.080)	0.420*** (0.083)	0.563*** (0.076)
Fulltime	-0.478*** (0.140)	-0.461*** (0.158)	-0.328** (0.136)	-0.428*** (0.130)
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.293	0.313	0.346	0.303
Observations	22939	22939	22939	22939

Notes: All models estimated are OLS with establishment and year fixed effects included. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 26: R3: Training participation - Exposure above median

Training participation	(1)	(2)	(3)	(4)
<u>Basic digital technologies:</u>				
RTI >50pct	-0.047* (0.026)			
Computerization >50pct		-0.098*** (0.021)		
<u>Advanced digital technologies:</u>				
AI Exposure >50pct			0.119*** (0.031)	
ML Suitability >50pct				0.037* (0.021)
<u>Control variables:</u>				
Age	-0.005*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)
Male	-0.021 (0.030)	-0.004 (0.029)	0.012 (0.032)	-0.005 (0.028)
Education	0.033*** (0.007)	0.028*** (0.008)	0.025*** (0.008)	0.031*** (0.007)
Qualification	0.014** (0.007)	0.011* (0.006)	0.010* (0.006)	0.015** (0.007)
Wage	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.001*** (0.000)
Firm size	-0.000 (0.000)	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)
Leadership	0.101*** (0.021)	0.097*** (0.019)	0.096*** (0.021)	0.104*** (0.019)
Fulltime	-0.019 (0.029)	-0.019 (0.030)	-0.012 (0.030)	-0.018 (0.026)
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.217	0.222	0.223	0.217
Observations	22970	22970	22970	22970

Notes: All models estimated are OLS with establishment and year fixed effects included. Demographic controls include gender, qualification, wage and establishment size. Computerization potential by Dengler & Matthes uses the kldb2010 occupational classification. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.