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journal homepage: [www.elsevier.com/locate/econedurev](http://www.elsevier.com/locate/econedurev)The effect of automation technology on workers' training participation<sup>☆</sup>Pascal Heß<sup>a,b,\*</sup>, Simon Janssen<sup>a</sup>, Ute Leber<sup>a</sup><sup>a</sup> Institute for Employment Research (IAB), Regensburger Str. 104, Nuremberg, 90478, Germany<sup>b</sup> Research Centre for Education and the Labor Market (ROA), Maastricht University, P.O. Box 616, Maastricht, 6200 MD, The Netherlands

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## ABSTRACT

We use detailed survey data to study the influence of automation technology on workers' training participation. We find that workers who are exposed to substitution by automation are 15 percentage points less likely to participate in training than those who are not exposed to it. However, workers who leave occupations that are highly exposed to automation increase their training participation, while those who enter them train consistently less. The automation training gap is particularly pronounced for medium-skilled and male workers, and is largely driven by the lack of ICT training and training for soft skills. Moreover, workers in exposed occupations receive less financial and nonfinancial training support from their firms, and the training gap is almost entirely related to a gap in firm-financed training courses.

## 1. Introduction

A large body of literature documents that technological change has a substantial impact on labor markets.<sup>1</sup> Particularly, leading automation technologies such as industrial robots have changed the wage and employment structure (e.g., Acemoglu, 2015; Acemoglu & Restrepo, 2017, 2018, 2020; Dauth et al., 2021), and emerging technologies such as artificial intelligence (AI) might even disrupt labor markets more substantially in the future.<sup>2</sup> Therefore, many scholars and practitioners emphasize the growing importance of on-the-job training and lifelong learning to prevent the disruptive effects of technological change, and governments worldwide are investing heavily in training policies (OECD, 2019). For example, in 2019, the German government spent approximately 2.1 billion Euros to subsidize further training.

However, evidence on the relationship between automation and on-the-job training is scarce. Nedelkoska and Quintini (2018) found a

large negative training gap for workers who are exposed to automation, but the results do not provide explanations for the lower training rate of affected workers. Instead, Innocenti and Golin (2022) show that workers who fear automation have a greater intention to participate in training.<sup>3</sup> However, firms, not workers, initiate and finance most on-the-job training,<sup>4</sup> and firms have different incentives than workers. On the one hand, firms might invest in training to facilitate the implementation of new technologies or retain firm-specific human capital.<sup>5</sup> On the other hand, firms may refrain from investing in training workers they plan to eventually replace with technology. Without understanding whether and, if so, how technological change influences workers' training participation, designing efficient training policies that are tailored toward the most affected workers is difficult.

This paper sheds light on the relation between automation technology and training by analyzing whether and why workers whose jobs are at a high risk of being changed or automated by industrial robots invest

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\* Corresponding author at: Institute for Employment Research (IAB), Regensburger Str. 104, Nuremberg, 90478, Germany.

E-mail addresses: [pascal.hess2@iab.de](mailto:pascal.hess2@iab.de) (P. Heß), [simon.janssen@iab.de](mailto:simon.janssen@iab.de) (S. Janssen), [ute.leber@iab.de](mailto:ute.leber@iab.de) (U. Leber).

<sup>1</sup> See Acemoglu and Autor (2011), Autor (2013), Autor et al. (2003), Goos and Manning (2007), Goos et al. (2014), Michaels et al. (2014) and Spitz-Oener (2006) for further evidence on the effects of technological change on labor markets.

<sup>2</sup> For example, Agrawal et al. (2019) argue that AI has particularly improved the quality of predictions that are involved in the decision-making of many high-skilled workers.

<sup>3</sup> Similarly, Acemoglu (1997) argued that workers are more willing to invest in training if they expect many firms to innovate because their returns to training increase with firms' innovation.

<sup>4</sup> Booth and Bryan (2007) reported that approximately 90 percent of all work-related training is firm-financed in Britain. Our data suggest a similar incidence of approximately 85 percent for Germany.

<sup>5</sup> A number of studies indeed have shown that technology implementation correlates with training investments on the firm level (e.g., Bresnahan et al., 2002; Sieben et al., 2009). Dixon et al. (2021) showed that firms adopting robots train assembly workers to take over tasks from their former, laid-off managers. Others showed that technology implementation leads to more job rotation (e.g., Caroli & Van Reenen, 2001).

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more or less in training. Therefore, we combine the adult survey of the National Educational Panel Study (NEPS) with a novel technology exposure measure by [Webb \(2020\)](#).

The NEPS data contain detailed survey information about workers' demographics, firm characteristics, labor market careers, and, most importantly, training participation. More specifically, we have information about the training content, frequency and duration, and we know whether and how firms support their workers' training. The technology exposure index of [Webb \(2020\)](#) allows us to identify the tasks compatible with the capabilities of current robot technology. It relies on the overlap between job task descriptions and patent applications to construct a measure of technology exposure on the occupational level.

First, we find a large negative training gap for workers who are highly exposed to robot technology. Even if we account for a huge set of observable characteristics (i.e., worker, job, and firm characteristics) and unobserved worker heterogeneity, the training gap still amounts to 4.2 percentage points. This gap is almost as large as the conditional on-the-job-training gap between college- and noncollege-educated workers ([Görlitz & Tamm, 2016b](#)). However, we find that workers who switch from occupations with high automation exposure to occupations with lower automation exposure increase their training participation once they enter the new occupation. This result is good news because it suggests that workers who are heavily exposed to automation technology, such that they have to switch occupations, receive the relevant training to cope with technology. However, if workers leave high-automation-exposed occupations for unemployment, they do not increase their training participation.

Second, we find that the training gap between workers in occupations with low and high automation exposure<sup>6</sup> is most pronounced among males and medium-skilled workers with an apprenticeship degree and that the greatest differences are for training courses in information and communication technologies (ICT) and soft and business skills.

Third, we find that workers in high-automation-exposed occupations receive substantially less financial and nonfinancial training support from their firms. Moreover, the automation training gap is entirely related to training courses that are fully financed by the workers' firms.

Our results contribute to at least two strands of the literature. First, we contribute to the literature on technological change. While previous studies have analyzed the wage and employment effects of technological change in general ([Acemoglu & Restrepo, 2018](#)) and robot technology in particular (e.g., [Acemoglu & Restrepo, 2020](#); [Dauth et al., 2021](#); [Dixon et al., 2021](#)), our study shows that automation has not only induced a polarization of the wage and employment structure but is also related to a polarization of workers' training participation. Thus, our results provide evidence for a channel through which technological change translates into a polarization of wages and employment. Moreover, if workers who are most likely to be exposed to the negative consequences of technological change invest less in training and retraining than other workers, the polarization of workers' training participation may reinforce the polarization of the wage and employment structure in the long run.<sup>7</sup>

Second, we contribute to the literature on the determinants of further training that has largely focused on the training gap between low- and high-educated workers (see e.g. [Fouarge et al., 2013](#); [Hidalgo et al., 2014](#); [Kramer & Tamm, 2018](#)). Instead, we show a large heterogeneity in the training participation of workers who have the same level of

<sup>6</sup> We use the words automation exposure and robot exposure interchangeably.

<sup>7</sup> This claim holds for positive wage and employment returns to training. Several papers find positive effects of training on wages and employment, e.g., [Görlitz and Tamm \(2016a\)](#) find positive effects on wages and [Schmidpeter and Winter-Ebmer \(2021\)](#) find that training improves the reemployment probabilities once workers have become unemployed. In contrast, [Schwerdt et al. \(2012\)](#) find no effects on wages or employment for Swiss voucher programs.

formal education but are sorted into occupations that differ in their risk of automation. The automation training gap is almost as large as the gap between low- and high-skilled workers ([Görlitz & Tamm, 2016b](#)).

By analyzing how workers' training participation responds to job switches and transitions to unemployment, we also provide novel evidence on the dynamics of training participation that complements the literature that has largely focused on static relationships. Moreover, in contrast to most previous papers, we are able to analyze the training content to show that the automation training gap is predominantly related to IT training and training for soft and business skills.

Third, we contribute to the literature on further work-related training by showing that firms finance and potentially initiate the largest share of training. Most previous papers have focused on individual determinants of training. For example, [Innocenti and Golin \(2022\)](#) showed that workers have greater intentions to train if they are exposed to automation, and [Caliendo et al. \(2022\)](#) showed that workers' locus of control has a strong influence on their training participation. Instead, our results suggest that firms may have a much larger influence on training participation than individual workers—even if they are exposed to potentially negative career outcomes. This result is similar to [de Grip et al. \(2020\)](#), [Görlitz and Tamm \(2017\)](#) or [van den Berg et al. \(2020\)](#), who also concluded that employees are not the primary decision-makers.

The remainder of this study is structured as follows. Section 2 provides some theoretical background for the relationship between automation exposure and workers' training participation. Section 3 describes our data and variables and provides the first descriptive evidence. Section 4 presents the methods, while Section 5 presents our results. Section 6 concludes.

## 2. Technological change and investments in on-the-job training

Many papers show that technological change has a substantial influence on labor markets, because new technologies change the demand for skills ([Autor et al., 2003](#)). The main purpose of automation technologies, particularly robots, is to automate tasks currently performed by workers. Therefore, automation technology is particularly powerful in performing routine codifiable tasks often present in large manufacturing firms. In contrast, tasks that cannot be automated by technology are generally complemented by it. Many tasks that complement emerging technologies are nonroutine tasks that involve creativity or complex reasoning, e.g., mathematics, computer programming and advanced IT skills ([Autor et al., 2003](#)). However, as [Deming \(2017\)](#) argues, social skills have also become increasingly important because they reduce coordination costs between ever more specialized workers in rapidly changing environments.

Employment is most likely to disappear in jobs with a very large proportion of automatable tasks. In contrast, most other jobs will change but not disappear, because the remaining nonautomatable tasks will continue to be essential for the productivity of firms ([Autor, 2015](#)). Obviously, incumbent workers in disappearing jobs have a large incentive to invest in skills that are valuable in other jobs and firms. However, rapidly changing occupations also require workers to learn many new tasks such that the gains from learning new skills diminish and the returns to experience decline over time. As a result, even workers in occupations that do not disappear but change rapidly have incentives to switch occupations and learn new skills if technological change accelerates ([Deming & Noray, 2020](#)).

Thus, while investments in occupation- and firm-specific skills might shield workers from the negative consequences of technological change if only a few tasks are replaced by technology, investments in general skills become more essential if many tasks can be substituted by technology. According to classical economic theory, workers and firms share their investment and returns in specific skills, but workers have to bear the entire cost of general human capital investments ([Becker, 1962](#)). However, in practice, continuous on-the-job training is related

to high opportunity costs for incumbent workers because they earn high wages and are likely to be time constrained by household obligations. Moreover, credit markets are imperfect such that borrowing for training investments is restricted, even if workers do not exhaust their credit (Cavounidis & Lang, 2020). Although employees can theoretically borrow from their firms, for example, by accepting lower wages, training contracts, future labor mobility, and future wages are difficult to enforce legally. As a result, workers' ability to invest in training is limited in practice, such that firms commonly finance the largest share of on-the-job training—even for training investments in general skills that are portable across firms and occupations (Acemoglu & Pischke, 1999).

As a number of studies show, firms have incentives to invest in general skills—e.g., if wage structures are compressed and labor mobility is low (e.g., Acemoglu & Pischke, 1998). However, firms' incentives to invest in their workers' general skills decline once workers become likely to switch occupations and firms. As a result, automation exposure might reduce firms' incentives to invest in their workers' training—particularly, in the general training.

### 3. Data and variables

This section describes our data and variables. The first subsection describes the adult starting cohort of the National Educational Panel Study (NEPS) containing training measures and variables on individual worker characteristics and firms. The second subsection describes the technology exposure data by Webb (2020) that we use to measure workers' exposure to automation by robots.

#### 3.1. The National Educational Panel Study (NEPS)

The adult starting cohort of the NEPS is a longitudinal study that surveys educational and labor market trajectories of approximately 10,000 adults between 2009 and 2020. We restrict our data to working individuals who do not undergo vocational training at the time of the interview and are between 25 and 60 years old. Finally, we deleted all observations with missing values in our main variables of interest. These restrictions leave us with 43,779 observations of 9,594 individuals.

Our dependent variables measure worker participation in nonformal training courses that are labor-related and occur throughout the workers' employment spells.<sup>8</sup> In more detail, our main dependent variable is a dummy variable indicating whether a worker participated in at least one training course during the last 12 months before the interview. Additionally, we analyze the frequency and duration of training to uncover effects at the intensive margin. We analyze the effects for different fields of training (e.g., ICT or soft skills training), we provide evidence for workers' formal training participation, and we analyze workers' training participation throughout unemployment spells.

In addition to our training measures, the NEPS contains a wide variety of individual and firm characteristics that have a strong influence on the training participation of workers according to many previous studies (e.g., Kramer & Tamm, 2018; Nelen & de Grip, 2009; Tamm, 2018). First, we have detailed information about the workers' gender, migration background, education, part-time employment, work experience, tenure, and wages. Second, in contrast to virtually all other large panel data sources, we have detailed information about their firms' financial and nonfinancial training support. In more detail, we know whether the workers' firms have an official training agreement or an official unit responsible for on-the-job training, and we know whether a firm has offered the individual worker financial or nonfinancial training support. More detailed descriptions of the variables and descriptive statistics of all variables appear in Appendix A.

<sup>8</sup> We exclude training that is not employment related, informal training that is not organized in courses or seminars, formal training such as apprenticeship training, and training courses that occur during periods of nonemployment.

#### 3.2. Exposure to robot automation

The main goal of our study is to analyze the influence of robot exposure on workers' training participation. To measure robot exposure, we use a new index by Webb (2020) that quantifies the share of tasks for each occupation that might be performed by robots. To create this measure, Webb (2020) combined information from patent texts with job descriptions from O\*Net. He used both data sources to find verb-noun pairs indicating an overlap between occupational tasks and the capabilities of new robot technologies according to patent texts. Thus, the measure considers occupations with a larger fraction of overlapping tasks as more exposed to robot technology than those with a lower fraction.

Many recent papers have used and validated Webb's measure for technology exposure (e.g., Acemoglu et al., 2022). For example, Webb (2020) himself found displacement effects of robot exposure on wages and employment that are similar to those found in studies using data from the International Federation of Robotics (IFR) (e.g., Acemoglu & Restrepo, 2018). Acemoglu et al. (2022) validated Webb's measure by comparing it with a variety of other technology exposure measures.

As Webb created the robot-exposure measure for U.S. occupations, we had to use a crosswalk between the Standard Occupational Classification (SOC) from the U.S. and the German classification of occupations from 2010 (see Appendix B). One concern might be that the tasks of German occupations differ from those of U.S. occupations. Therefore, Appendix C replicates our analysis with an index from Dengler et al. (2014). This index measures to what extent automation technology can replace occupational tasks. Dengler et al. (2014) designed the measure explicitly for the German occupational structure using the German task data base BERUFENET. Although the BERUFENET measure does not exclusively focus on robots, it is reassuring that both measures significantly correlate (0.34).<sup>9</sup>

Webb's measure assigns each occupation to its exposure percentile. For example, a value of 50 indicates that the occupation is the median occupation of being likely to be automated by robots. Table 1 shows the sample composition along the distribution of robot exposure in our sample. In more detail, we compare the shares of gender, education, and age groups within quartiles for the first NEPS wave in 2009.

Table 1 shows that women are less likely to work in robot-exposed jobs than men. For example, 56 percent of all workers in occupations that are below the 25<sup>th</sup> percentile in the Webb measure are women, but only 39.9 percent in occupations that are above the 75<sup>th</sup> percentile. This holds true for workers without a vocational or apprenticeship degree. While workers without vocational degrees disproportionately often work in jobs with very high robot exposure ( $\geq p75$ ), very few workers with university degrees work in such jobs.

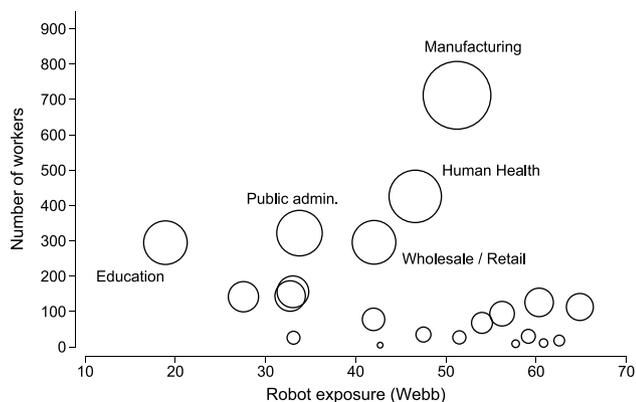
Fig. 1 shows the distribution of robot exposure across industries relative to the size of the industries in our data. The y-axis shows the number of workers in each industry, and the x-axis shows the average robot-exposure scores within each industry. The figure reveals that the average robot exposure is relatively high in the manufacturing sector—the largest sector in our data. In contrast, the sectors of education, public administration, and financial services have, on average, lower robot-exposure scores. The wholesale and retail sector lies in the middle of the exposure distribution, and a number of small industries have, on average, even larger exposure scores than the manufacturing sector. For example, the relatively small sector of professional cleaning services has an average exposure score of 65 because the innovation of robot technology for cleaning has accelerated throughout recent years, i.e., robot technology cleaning surfaces of large buildings (Zhang et al., 2007).

<sup>9</sup> The measure by Dengler et al. (2014) does not directly relate to industrial robots, and tasks are classified based on the judgment by a small set of experts. Thus, we decided to retain Webb's measure for our main analysis.

**Table 1**  
Sample statistics along the robot-exposure distribution.  
Source: Source: NEPS-SC6 13.0.0, own calculation.

	<p25	[p25; p50)	[p50; p75)	≥p75
<i>Gender</i>				
Men	.440	.410	.632	.601
Women	.560	.590	.368	.399
<i>Education</i>				
No Vocational Degree	.030	.072	.077	.164
Apprenticeship Degree	.392	.704	.764	.768
University Degree	.578	.225	.159	.069
<i>Age</i>				
Born 1980 and above	.172	.157	.167	.144
Born 1970–1979	.193	.178	.217	.177
Born 1960–1969	.265	.264	.289	.259
Born 1950–1959	.370	.401	.327	.421
Observations	830	1184	508	611

This Table shows the sample composition for gender, education, and age for different quartiles of the distribution of Webb’s (2019) robot-exposure measure for the first wave.

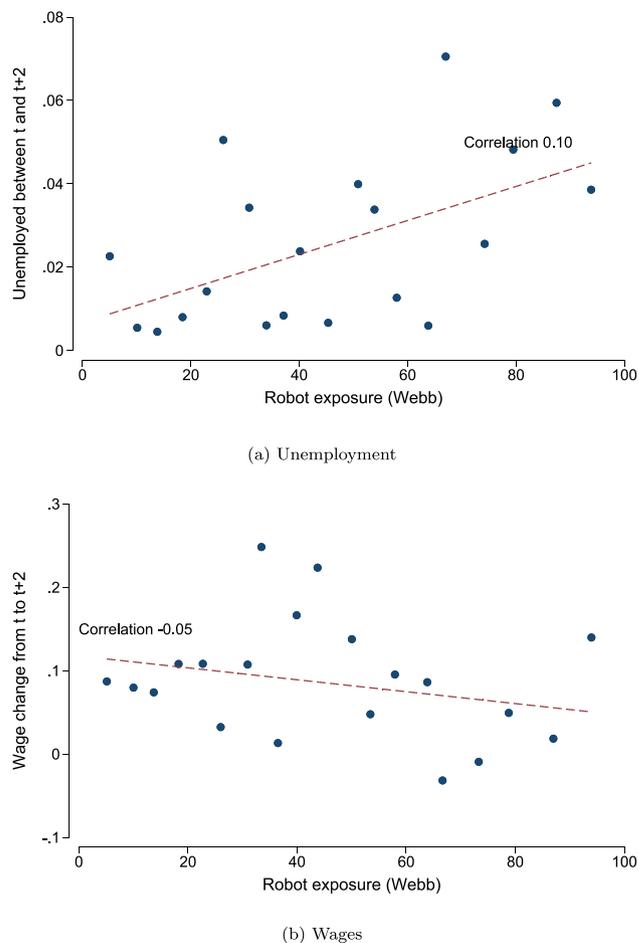


**Fig. 1.** Distribution of robot exposure across industries. The figure shows the distribution of robot exposure across industries in the first NEPS wave. The size of the circles indicates the number of workers. The names of the five largest industries are shown in the figure.  
Source: NEPS-SC6 13.0.0, own calculation.

Although the literature documents for the U.S. that Webb’s automation-exposure measure relates negatively to wages and employment, this relationship has not yet been documented for Germany (Webb, 2020). However, if automation exposure does not have any influence on workers’ career prospects in Germany, we should not expect an impact on their decision to participate in further training. Therefore, Fig. 2 describes the relationship between automation exposure, wage growth, and future unemployment in the NEPS data. Panel (A) shows the relationship between workers’ automation exposure in  $t$  (x-axis) and their wage growth between  $t$  and  $t + 2$  (y-axis). Panel (B) shows the relationship between automation exposure at time  $t$  and their likelihood of experiencing at least one unemployment spell between  $t$  and  $t + 2$ . The results reveal that automation exposure relates negatively to future wage growth and positively to future unemployment. Thus, automation exposure is related to worse career prospects, such that workers’ incentives to train should rise with automation exposure.

**4. Methods**

A large number of observable and unobservable characteristics are likely to influence both workers’ training participation and their exposure to robot technology. Unfortunately, robot exposure is a function



**Fig. 2.** Unemployment and wages. The figure shows the correlation between robot exposure and future unemployment (a) and wages (b). The y-axis of Panel (a) indicates the workers’ wage growth between  $t$  and  $t + 2$ . The y-axis of Panel (b) indicates the share of workers who experience at least one spell of unemployment between  $t$  and  $t + 1$ . The x-axis denotes the robot exposure measure by Webb (2019).  
Source: NEPS-SC6 13.0.0, own calculation.

of occupational tasks, and workers do not tend to choose their jobs randomly. As a result, finding quasiexperimental variation to identify the causal effect of robot exposure on workers' training participation is very difficult, if not impossible. Therefore, we have to rely on panel data estimators and control variables to capture as many observable and unobservable confounding factors as possible.

More specifically, we regress the workers' training participation on Webb's robot exposure according to the following equation:

$$T_{it} = \delta Robot_{it} + Industry_{it}\beta_1 + Job_{it}\beta_2 + Firm_{it}\beta_3 + Individual_i\beta_3 + \mu_i + \lambda_t + \epsilon_{it} \quad (1)$$

Our main dependent variable  $T_{it}$  measures whether workers undertook at least one training course throughout the last 12 months. In addition, we analyze workers' training intensity (i.e., training hours or number of training courses), their training content (e.g., IT training or soft/business skill training), and whether workers underwent formal training (i.e., apprenticeship or university degree).

The main explanatory variable  $Robot_{it}$  is Webb's robot-exposure score, and  $\delta$  is our main coefficient of interest. We use a continuous and a dichotomous version of the robot-exposure measure  $Robot_{it}$ . The continuous measure assigns a score to each occupation that equals the occupation's percentile in the distribution of robot exposure. The dichotomous measure is a dummy variable that equals 1 if an occupation is above the 70<sup>th</sup> percentile of the exposure measure and 0 otherwise.

As occupations are clustered across industries, unrelated demand shifts on the industry level—particularly international trade—might confound with the influence of technological change on the occupational level. Therefore, we follow Webb (2020) and account for industry fixed effects in each specification.

The variables  $Job_{it}$ ,  $Firm_{it}$ , and  $Individual_i$  comprise several job, firm, and individual characteristics that are not directly related to a firm's training policy.  $Job_{it}$  represents a set of time-varying job characteristics, including dummy variables for part-time and public employment, a quadratic function for experience, and a categorical variable for working hours.  $Firm_{it}$  contains a categorical variable for firm size.  $Individual_i$  contains time-constant individual characteristics, i.e., education, gender, migration background, and year of birth. Finally,  $\mu_i$  displays individual worker fixed effects to capture time-constant unobserved heterogeneity at the worker level,  $\lambda_t$  are time fixed effects, and  $\epsilon_{it}$  is the error term. Standard errors are clustered at the individual level.

## 5. Results

This section presents the results of our paper in seven subsections. The first subsection shows our main results. The second subsection presents the dynamic effects for workers who switch occupations or become unemployed. The third subsection shows the heterogeneous effects for different groups of workers. The fourth subsection analyzes the intensive margin of workers' training participation. The fifth subsection analyzes the effects of different training contents, the sixth subsection analyzes formal training, and the seventh subsection analyzes whether workers receive financial and nonfinancial training support from their firms.

### 5.1. Main results

Fig. 3 shows the relationship between workers' training participation on the y-axis and the percentiles of robot exposure on the x-axis. The solid black line indicates the average training participation in our sample.

The figure reveals that workers who are highly exposed to substitution by robot technology train, on average, substantially less than those who are less exposed to it. More specifically, workers below the 70<sup>th</sup>

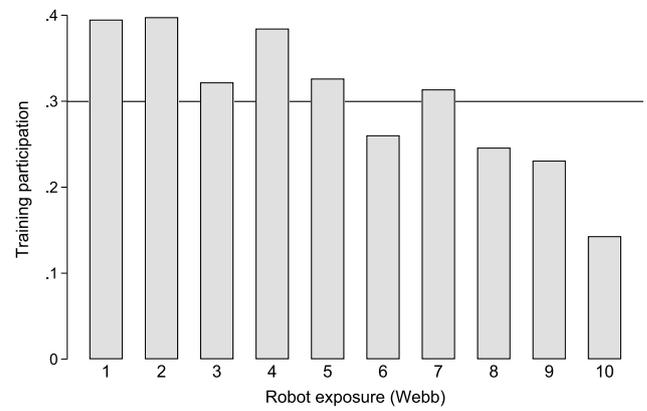


Fig. 3. Relationship between robot exposure and training. The figure shows the training participation rate along the robot-exposure distribution. The horizontal line indicates the sample average training participation across all waves. Source: NEPS-SC6 13.0.0, own calculation.

percentile of robot exposure have an average rate of training participation that is close to the mean training participation rate of approximately 30 percent or substantially above (e.g., approximately 40 percent). In contrast, workers in the highest percentiles of robot exposure (i.e., above the 70<sup>th</sup> percentile) have substantially lower participation rates of less than 25 percent, on average.

To quantify the visual correlation from Fig. 3, Table 2 shows a set of results from regression Eq. (1). Panel A of Table 2 displays the results from a specification with the continuous measure for robot exposure, and Panel B displays the training gap between workers in jobs with high robot exposure (i.e., above the 70<sup>th</sup> percentile) and lower robot exposure.

Column I shows the OLS results that only account for industry and year dummies to control for nonlinear industry and time trends. The coefficient estimate for robot exposure is  $-0.022$ , and it is precisely estimated at the one percent level. Thus, a 10 point increase in the percentile of robot exposure is associated with a reduced training participation of approximately two percentage points. Panel B shows that the training gap between those with high (above the 70<sup>th</sup> percentile) and low levels of robot exposure is approximately 12 percentage points. Thus, workers who are highly exposed to substitution by robot technology train 40 percent less often than the average worker.

Column II accounts for education. Previous literature shows that low-educated workers, on average, train less than high-educated workers (e.g. Bassanini et al., 2007; Fouarge et al., 2013). As low-educated workers are also more likely to work in occupations with higher robot exposure, the negative effect of Column I might be the consequence of low-educated workers self-selecting into occupations with greater robot exposure. However, the coefficient estimate for the continuous measure in Column II is still  $-0.018$ , and the training gap between high- and low-exposure workers remains at 10 percentage points. These results suggest that educational differences account for only a small share of the training gap. Similarly, Columns III and IV suggest that accounting for time-constant individual worker characteristics, such as gender and migration status and job and firm characteristics, does not substantially change the results. In contrast, Row V reveals that the effect declines by more than half if we account for unobserved time-constant heterogeneity at the worker level. The fixed effects regression reveals an effect of 0.6 percentage points for the continuous measure and 5 percentage points for the training gap between low- and highly exposed workers.<sup>10</sup>

<sup>10</sup> This fixed effects regression does not control for education and individual characteristics because these are time-constant variables.

**Table 2**  
Effect of robot exposure on training participation.  
Source: Source: NEPS-SC6 13.0.0, own calculation.

	I	II	III	IV	V
	<i>Panel A: continuous measure</i>				
Robot-exposure percentile	-0.022*** (0.001)	-0.018*** (0.001)	-0.017*** (0.001)	-0.015*** (0.001)	-0.006** (0.002)
R <sup>2</sup>	0.055	0.058	0.059	0.069	0.022
	<i>Panel B: dichotomous measure</i>				
High robot exposure	-0.122*** (0.007)	-0.102*** (0.007)	-0.098*** (0.007)	-0.090*** (0.007)	-0.048*** (0.014)
R <sup>2</sup>	0.054	0.058	0.059	0.070	0.022
Education	No	Yes	Yes	Yes	No
Individual controls	No	No	Yes	Yes	No
Job characteristics	No	No	No	Yes	Yes
Firm characteristics	No	No	No	Yes	Yes
Individual f.e.	No	No	No	No	Yes
Observations	47350	47350	47350	47350	47350

Dependent variable: Training participation (yes/no). Column I shows results for an OLS version of Eq. (1) without individual fixed effects and other controls. Column II includes education. Column III includes education and other individual controls (gender, migration background, age). Columns IV adds job and firm Characteristics and Column V uses individual fixed effects as specified in Eq. (1). All regressions include time fixed effects and industry fixed effects. Standard errors in parentheses are clustered on the individual level. \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ .

The fixed-effects specification in Column V identifies the effect of automation exposure from variation of job switchers because robot exposure is measured on the occupational level. Appendix D reveals that workers who switch from high- to low-automation-exposure occupations might be slightly positively selected relative to those who switch from low- to high-automation-exposure occupations. As a result, the additive structure of our fixed effects models might be misspecified (see Card et al., 2013) because the unobserved factors (e.g., ability) that drive the selection of workers out of high-automation-exposure occupations might have a dynamic impact on workers’ training participation. To surmount this worry, Appendix D provides a detailed discussion of how this selection problem might influence our coefficient estimates, and it presents three additional robustness checks. None of these robustness checks suggest that the additive structure of our fixed effects models is violated.

Nevertheless, a training gap of approximately 5 percentage points is still sizable and economically significant. First, the training gap amounts to 16 percent of the average training participation. Second, the training gap is approximately half as large as the unconditional training gap between high- and medium- or medium- and low-skilled workers in Germany (Kramer & Tamm, 2018).

Innocenti and Golin (2022) use survey data from 16 countries to show that workers who are exposed to the risk of automation and workers in occupations that are exposed to automation have greater intentions of investing in training, particularly outside their workplaces. In contrast, Table 2 reveals that these workers train substantially less than workers in less-exposed occupations. This contrast might suggest that workers in automation-exposed occupations are too credit constrained to invest in training, even though they would be willing to do so.

### 5.2. Dynamic results and transitions into unemployment

This section presents dynamic results by analyzing the effect of automation exposure on workers’ future training participation through the periods between  $t$  and  $t+3$ . This approach also allows us to consider transitions to unemployment. More specifically, we estimate regression equations of the following form:

$$T_{it+s} = \delta_1 SwitchOcc_{it,t+1}^{h,l} + \delta_2 SwitchUnemp_{it,t+1} + X_{it}\beta + \lambda_t + \epsilon_{it} \quad (2)$$

$T_{it+s}$  is our training measure as defined in Section 4. However, instead of measuring workers’ training participation at time  $t$ ,  $T_{it+s}$  measures workers’ training participation at time  $t + s$  with  $s \in (0, 1, 2, 3)$ .  $SwitchOcc_{it,t+1}^{h,l}$  is a dummy variable indicating whether a worker

switches into an occupation with a different automation-exposure level between  $t$  and  $t + 1$ .  $l$  indicates switches from low- to high-exposure occupations, and  $h$  indicates switches from high- to low-exposure occupations.  $SwitchUnemp_{it,t+1}$  indicates whether workers switch from employment to unemployment between  $t$  and  $t + 1$ . We estimate Eq. (2) for two samples. One sample only includes workers who are in high-exposure occupations at time  $t$ , and one only includes workers who are in low-exposure occupations. Thus, we measure  $\delta_1$  and  $\delta_2$  relative to workers who remain in high- (low-) exposure occupations.  $X_{it}$  denotes the same control variables as described in Section 4.  $\lambda_t$  are year dummies, and  $\epsilon_{it}$  is the error term. We do not include individual fixed effects in Eq. (2) to assess the differences between occupational switchers and stayers.

Panel A of Table 3 presents the results for workers in occupations with high automation exposure, and Panel B presents the results for workers in occupations with low automation exposure. The first and fourth rows present the effect for occupation switches. The first column presents the effect of a switch between  $t$  and  $t + 1$  on training participation in  $t$ . This approach is akin to testing for pretrends and infers whether workers have already changed their training participation in anticipation of a switch. As we do not find a significant effect for occupation switches, the results do not suggest that workers change their training behavior in anticipation of an occupational switch.

In contrast, workers who switch out of occupations with high automation exposure into occupations with low automation exposure increase their training participation in  $t+1$  by approximately 8 percentage points relative to those who remain in high-exposure occupations, and workers who switch from low- to high-exposure occupations reduce their training participation by approximately 8 percentage points in  $t+1$ . Thus, both effects point in different directions but are very similar in magnitude. Moreover, the magnitude of both effects is similar to the magnitude of the coefficient estimate in the full saturated OLS estimation in specification III of Table 2. Thus, the results of Table 3 clearly suggest that automation exposure has an additive effect on workers’ training participation and is not driven by more able workers switching out of occupations with high automation exposure. However, the positive training effect for workers who switch from high- to low-exposure occupations vanishes in  $t+2$  and  $t+3$ . In contrast, the negative effect for workers who switch from low- to high-exposure occupations remains large and precisely estimated.

Rows two and five show the coefficient estimates for transitions into unemployment. We find a positive effect in the first column of the second row that is marginally significant at the 10 percent level. This effect suggests that workers in high-exposure occupations train

**Table 3**  
Effect of switching occupations and unemployment on future training participation.  
Source: Source: NEPS-SC6 13.0.0, own calculation.

	t	t+1	t+2	t+3
<i>Panel A: Workers in high-exposure occupations</i>				
To low exposure	0.017 (0.037)	0.075** (0.038)	-0.009 (0.036)	-0.015 (0.035)
To unemployment	0.127* (0.077)	0.081 (0.069)	-0.071 (0.044)	0.005 (0.059)
N	3345	3345	3345	3345
<i>Panel B: Workers in low-exposure occupations</i>				
To high exposure	0.025 (0.043)	-0.084** (0.040)	-0.089** (0.039)	-0.074* (0.039)
To unemployment	-0.054 (0.070)	-0.152*** (0.056)	-0.119* (0.068)	-0.065 (0.066)
N	11773	11773	11773	11773

Dependent variable: Future training participation between  $t$  to  $t + 3$ . All columns show OLS regressions with full set of control variables as specified in Eq. (1). Panel A shows results for future training for workers switching from high-exposure occupations to low-exposure occupations or to unemployment from  $t$  to  $t+1$ . The reference group includes workers staying in high-exposure occupations. Panel B shows results for future training for workers switching from low-exposure occupations to high-exposure occupations or to unemployment from  $t$  to  $t+1$ . The reference group are workers staying in low-exposure occupations. Column one to four show the results for training participation between  $t$  and  $t + 3$ . Standard errors in parentheses are clustered on the individual level. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

somewhat more before becoming unemployed. However, we do not find effects for  $t + 1$  throughout  $t + 3$ . In contrast, workers who switch from low-exposure occupations to unemployment substantially reduce their training participation by more than 10 percentage points in the medium run.

Overall, the results suggest that workers who are highly exposed to automation receive the relevant training to cope with the new environment if they manage to find a job in a less-exposed occupation. Instead, they appear not to train in anticipation of a potential displacement, and they do not increase their training incentives during periods of unemployment. Workers who leave occupations with low automation exposure even substantially reduce their training participation. This result suggests that many workers might not pick up one of the many government subsidies for training participation—not even if they become unemployed.

### 5.3. Intensive and extensive margin

Table 4 exploits our data in more detail by analyzing the intensive margin of workers’ training participation, i.e., their hours spent in training courses and the number of courses per year. Column I shows the effect for working hours on a sample that includes all workers, i.e., also those who do not train. Column II shows the effect on a sample that only includes workers who train. Columns III and IV replicate this analysis for the number of training courses. All specifications, except Column II, show a negative effect of robot exposure on the training intensity. However, only Columns I and III show an effect that is precisely estimated at conventional levels. Thus, the results from Table 4 suggest that robot exposure has a larger effect on the workers’ decision of whether to train than on their training intensity.

### 5.4. Heterogeneous effects

Exposure to automation might have different effects for different types of workers. For example, high skilled workers might be less exposed to the negative consequences of automation and more capable of training and retraining than low-skilled workers. Men might be more exposed to automation than women because they are more likely to work in production.

To obtain a more nuanced view of who is affected by high robot exposure, Table 5 shows the results of regression Eq. (1) separately for low (no degree), medium (apprenticeship degree), and high-skilled workers (university degree) for men and women. The results show a small negative effect of robot exposure on training participation for

low- (Column I) and high-skilled workers (Column III) that is not statistically significant at conventional levels. In contrast, they reveal a large negative effect for medium-skilled workers with an apprenticeship degree that is precisely estimated (Column II).<sup>11</sup> Columns IV and V reveal that the training gap is much larger for men than for women.

These results are consistent with a number of papers showing that the negative consequences of technological change have a greater influence on men, particularly medium-skilled men, than on women. For example, Black and Spitz-Oener (2010) show that technological change substantially contributed to the closing of the gender wage gap. Moreover, Cortes et al. (2021) explain the closing of the gender wage gap with the growing importance of social skills in response to increasing technological change. As we show in the next subsection, the training gap is indeed most pronounced for training for social skills.

### 5.5. Training content

This subsection analyzes the influence of robot exposure on training participation in four different training categories. The first category contains IT training courses for IT, computer, and data processing skills. Many view IT skills as the new literacy (e.g., Neelie Kroes, former Vice President of the European Commission), and IT skills are related to substantial wage returns for individual workers (e.g., Falck et al., 2021). Thus, IT skills appear to be important for career development in times of fundamental technological change. The second training category is for production technologies and processes. Production technologies are often specific to the production process within the firm or sector.

The third category contains courses for soft skills and business administration, including courses for presentation skills, linguistic proficiency, and business administration. Emerging literature shows the rising importance of soft and management skills, including communication, teamwork, presentation, customer relations and leadership skills. Throughout recent decades, the wage returns to soft skills have risen even more strongly than the returns to analytical or IT skills (e.g., Deming, 2017; Deming & Kahn, 2018). The fourth category contains all other training courses.

Table 6 reveals that workers who are highly exposed to robot technology are significantly less likely to invest in IT training and

<sup>11</sup> Apprenticeship graduates are skilled workers with a dual education that alternates between firm and classroom training. Apprenticeship training programs usually last three years and are comparable to U.S. four-year colleges that provide high-skilled vocational education. Approximately 60 percent of all workers in Germany hold an apprenticeship degree.

**Table 4**  
Extensive and intensive margin of training intensity.  
Source: Source: NEPS-SC6 13.0.0, own calculation.

	I Ext. Hours	II Int. Hours	III Ext. Number	IV Int. Number
High robot exposure	-2.330* (1.328)	1.539 (6.946)	-0.107** (0.042)	-0.152 (0.201)
R <sup>2</sup>	0.010	0.014	0.018	0.020
Observations	47350	14189	47350	14189

Dependent variables: Hours spent in training courses, number of courses. All columns show results for a version of Eq. (1) using different dependent variables. Columns I and II show results for the hours spent in training as the dependent variable. Columns III and IV show results for the number of courses as the dependent variable. Columns I and III show results for the extensive margin, i.e., unconditional on training participation. Columns II and IV show results for the intensive margin, i.e., conditional on training participation. All regressions include individual fixed effects and time fixed effects. Standard errors in parentheses are clustered on the individual level. \* $p < 0.1$ ; \*\* $p < 0.05$ .

**Table 5**  
Heterogeneity analysis.  
Source: Source: NEPS-SC6 13.0.0, own calculation.

	Education			Gender	
	I	II	III	IV	V
	Low	Medium	High	Male	Female
High robot exposure	-0.022 (0.035)	-0.051*** (0.016)	-0.053 (0.038)	-0.078*** (0.021)	-0.024 (0.019)
R <sup>2</sup>	0.027	0.022	0.030	0.023	0.023
Observations	2824	30337	14189	22921	24429

Dependent variable: Training participation. All columns show results for Eq. (1) for different subsamples. Columns I, II, and III show results for the groups of low (no vocational degree), medium (apprenticeship degree), and high (university degree) educated. Columns IV and V show results for male and female workers. All regressions include individual fixed effects and time fixed effects. Standard errors in parentheses are clustered on the individual level. \*\*\* $p < 0.01$ .

**Table 6**  
Effect of robot exposure on training by content.  
Source: Source: NEPS-SC6 13.0.0, own calculation.

	I	II	III	IV
	IT	Production	Soft/Business	Other
High robot exposure	-0.020*** (0.007)	-0.004 (0.008)	-0.034*** (0.010)	-0.024* (0.013)
R <sup>2</sup>	0.009	0.006	0.015	0.013
Observations	35560	34882	38154	47350

Dependent variable: Training participation. All columns show results for Eq. (1) for different types of training content. The indicator for training participation is 1 if the respondent has participated in a course in the last 12 months specified as IT (Column I), production (Column II), doft/business (Column III), or others (Column IV), and 0 if the respondent has not participated in any course in the last 12 months. All regressions include individual fixed effects and time fixed effects. Standard errors in parentheses are clustered on the individual level. \* $p < 0.1$ ; \*\*\* $p < 0.01$ .

training for soft and business skills than other workers. IT and soft skills are general and can be transferred across firms, occupations, and industries. While IT training benefits individual productivity, social skills reduce coordination costs and benefit team productivity (Deming, 2017). Moreover, as mentioned above, recent literature suggests that firms demand a complementary cognitive and social skill set (Deming & Kahn, 2018). Thus, these skills are important for workers' career development. However, firms might have relatively low incentives to invest in these skills when workers are likely to be replaced by technology. For training in production technologies, which is often firm-specific, and for other training fields, we find no significant negative effects.

### 5.6. Formal training

If workers are likely to be replaced by robot technology in the near future, both workers and firms might have very low incentives to invest in nonformal on-the-job training because workers are very likely to change their firm and occupation. However, workers who are likely to be displaced from their current job might have high incentives to invest in formal training (i.e., to undertake a second apprenticeship training or to acquire a university degree) so that they can switch their occupation.

Therefore, Table 7 replicates the results of Table 2 for workers' formal training participation, i.e., the dependent variable is a dummy variable indicating whether the worker undertook an apprenticeship or university degree. The raw OLS results in the first column of Table 7 reveal a significant negative gap in the workers' formal training participation of approximately 0.2 percentage points, which amounts to approximately 40% of the control group mean. However, the gap disappears once we control for education and individual characteristics (Column III).

### 5.7. Firms' training support

Firms' financial and nonfinancial training support is an essential determinant of workers' training participation because workers' ability to finance their own on-the-job training is limited in practice. Incumbent workers have high opportunity costs because they earn high wages and they often appear to be credit constrained (Acemoglu & Pischke, 1999; Cavounidis & Lang, 2020).

Therefore, Table 8 presents the results of estimations of regression Eq. (1) on a set of dummy variables that describe the firms' general and individual training support. More specifically, we analyze four forms

**Table 7**  
Effect of robot exposure on formal further training participation.  
Source: Source: NEPS-SC6 13.0.0, own calculation.

	I	II	III	IV	V
High robot exposure	-0.002*** (0.001)	-0.002** (0.001)	-0.002** (0.001)	-0.000 (0.004)	0.000 (0.004)
R <sup>2</sup>	0.0031	0.0034	0.0074	0.0022	0.0028
Education	No	Yes	Yes	Yes	No
Individual controls	No	No	Yes	Yes	No
Job Characteristics	No	No	No	Yes	Yes
Firm Characteristics	No	No	No	Yes	Yes
Individual FE	No	No	No	No	Yes
Observations	47350	47350	47350	47350	47350

Dependent variable: Formal training participation. All columns show results for Eq. (1) with further formal training as the dependent variable. Formal training is defined as undergoing regular vocational education (apprenticeship/university degree). The indicator for formal training participation is 1 if the respondent has started further formal training in the last 12 months, and 0 if the respondent has not started formal further training in the last 12 months. Column I shows results for an OLS version of Eq. (1) without individual fixed effects and other controls. Column II includes Education. Column III includes Education and other Individual controls (gender, migration background, age). Columns IV adds Job and Firm Characteristics and Column V uses individual fixed effects as specified in Eq. (1). All regressions include time fixed effects and industry fixed effects. Standard errors in parentheses are clustered on the individual level. \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

**Table 8**  
Effect of robot exposure on training support.  
Source: Source: NEPS-SC6 13.0.0, own calculation.

	General support				Individual support	
	Agreement I	Planning II	Financing III	Person IV	Leave Work V	Financing VI
High robot exposure	-0.102*** (0.034)	-0.161*** (0.035)	-0.141*** (0.034)	-0.114*** (0.034)	-0.131*** (0.035)	-0.105*** (0.037)
R <sup>2</sup>	0.028	0.034	0.054	0.040	0.042	0.035
Observations	15484	15484	15484	15484	15484	15484

Dependent variables: Training support. General training support includes whether (I) the firm sets contractual agreements to train, (II) the firm has a plan when to train whom, (III) the firm has a general budget for further training, and (IV) the firm has a person or department responsible for further training issues. Individual support includes whether the firm supports the individual (V) by granting leave hours during training or (VI) supports the training financially. All regressions include the full set of covariates, individual and time fixed effects. Standard errors in parentheses are clustered on the individual level. \*\*\* $p < 0.01$ .

of general firm support for training that is not directly targeted to the individual worker and two forms of direct individual training support by the firm. The dependent variables for general firm support indicate whether firms have (1) an official training agreement, (2) educational planning on the firm level, (3) general financing and provisions of training courses, and (4) an official unit responsible for on-the-job training. The dependent variables for individual support indicate whether the firm has offered the individual worker (1) a release from work to attend training and (2) to pay for training courses. The detailed questions appear in Appendix E. For these analyses, we can only use waves 2011/12, 2018/19, 2019/20, and 2020/21 because only those four waves contain detailed information about training policies at the firm.

Columns one throughout four show the results for general firm support. The results reveal that workers in highly automation-exposed occupations are less likely to work in firms that offer general training support. For example, highly exposed workers are 16 percentage points less likely to report that the firm has a training plan for employees.

Columns five and six report the results of firms' individual training support. The results reveal that workers in high-automation-exposure occupations are approximately 13 percentage points less likely to be offered a release from work for training and 10 percentage point less likely to receive offers for financial training support.

Given that we find such a strong relationship between automation exposure and firms' training support, the question arises whether the automation training gap is related to firm-financed or non firm-financed training courses. Therefore, Table 9 analyzes the automation training gap for firm-financed and non firm-financed training courses. More specifically, the first column of Table 9 shows estimations from regression Eq. (1) for training that is fully firm-financed, the second column for training that is partly firm-financed, and the third column

for training that is not firm-financed. Training that is not financed by the firm might be financed by the individual or by the government, for example, through one of the many training subsidies that are provided by the German government.

First, Table 9 shows that approximately 83 percent of all training courses are entirely firm financed. This outcome is comparable with the results for many other countries (Booth & Bryan, 2007). Four percent of the training courses are partly firm financed, and only 10 percent of the training courses are not financed by the firm. This result already suggests that firms have a substantial influence on workers' training participation.

The regression results reveal a precisely estimated training gap of approximately 4 percentage points for training that is entirely firm financed. Instead, we cannot find any effect for training courses that are partially firm financed or for training courses that are not financed by the firm. These results are consistent with studies arguing that workers are restricted in their ability to finance their own on-the-job training (Acemoglu, 1997; Acemoglu & Pischke, 1999; Cavounidis & Lang, 2020). Moreover, the results do not suggest that workers replace the lack of financial training support of firms with training support from the government.

## 6. Conclusion

Policy-makers around the world are concerned about the potential negative effects of automation. This paper shows that workers who are highly exposed to robot technology train substantially less than other workers, and neither common observable characteristics, such as education and experience, nor time-constant heterogeneity can entirely explain the training gap. However, workers who manage to switch from

**Table 9**  
Effect of robot exposure on firm-financed training participation.  
Source: Source: NEPS-SC6 13.0.0, own calculation.

	Fully firm-financed	Partly firm-financed	Not firm-financed
High robot exposure	−0.039*** (0.013)	0.002 (0.003)	−0.003 (0.005)
R-square	0.016	0.0026	0.0026
Observations	47350	47350	47350
Percentage of training courses	83%	4%	10%

Dependent variables: Dependent variable: training participation by financing of firms, OLS regressions with standard errors clustered on individual level, fixed effect regressions with individual fixed effects and standard errors clustered on individual level. All regressions include time fixed effects. Standard errors in parenthesis; All regression include time dummies \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

highly exposed occupation to less exposed occupation increase their training participation in the new firms.

The effect is mainly driven by medium-skilled and male workers and cannot be explained by training substitution strategies toward further formal training (catching up on, for example, university degrees). However, the training gap does not persist into the intensive margin (hours and number of training incidences)—that is, the bottleneck for workers in occupations with high exposure to robots is the initial training decision.

Our detailed survey data show that the lower training participation rate is concentrated among relevant skills, such as IT (Falck et al., 2021) or soft and business skills (Deming, 2017; Deming & Kahn, 2018). This may be problematic, as it magnifies inequalities resulting from the worker selection process. Workers who select high robot-exposure occupations are less likely to receive general training that is valuable in different occupations.

Overall, our results suggest that firms reduce their training investments for workers whom they plan to substitute by technology, and workers appear not to compensate for the lack of their firms’ training support by individual training investments. This lack of training investment might have negative effects on workers’ careers in the long run. Therefore, our results help to understand why workers who are replaced by modern technologies experience long-lasting negative consequences and do not adjust immediately (e.g., Cortes, 2016).

**CRedit authorship contribution statement**

**Pascal Heß:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing, Visualization. **Simon Janssen:** Conceptualization, Methodology, Software, Validation, Formal analysis, Writing, Visualization, Supervision, Funding acquisition. **Ute Leber:** Conceptualization, Validation, Formal analysis, Investigation, Writing, Visualization, Project administration, Funding acquisition.

**Data availability**

The authors do not have permission to share data.

**Appendix A. Descriptive baseline statistics**

See Table A.1.

**Appendix B. Webb scores–Crosswalk**

Webb (2020) delivers raw scores of the exposure level of occupations to software, robots, and AI, alongside the percentiles of each occupation. To crosswalk the raw data from Webb to the German classification of occupations, we first create a crosswalk for the Standard Occupational Classification (SOC) 2010 to the German Classification of Occupations (KldB) 2010 by using the International Standard Classification of Occupations (ISCO) 2008. Hardy et al. (2018) provide data on the crosswalk from SOC2010 to ISCO08. We use the official

crosswalk data from the Federal Employment Agency (BA) in Germany to crosswalk ISCO08 to KLDDB2010.

We then take the raw data obtained from Webb (2020) and trim the 8-digit O\*NET SOC-Code to 6 digits. Since several occupations have the same 6-digit code, we take the median exposure score of the duplicates. Afterward, we merge the 6-digit SOC to 5-digit KLDDB2010 using the crosswalk created in the first step and aggregate the data to the KLDDB2010 level, taking the median exposure score for each 5-digit KLDDB2010 level.

The following occupations do not receive any exposure score: occupations of the armed forces, coach drivers, chimney sweepers, professions in money and pawn lending, members of legislative bodies, professions in community work, members of religious orders and mother houses, professions in theology and congregational work, professions in moderation and entertainment, comedians and cabaret artists, magicians and illusionists.

**Appendix C. Replication with BERUFENET**

Fig. C.1 shows the correlation between Webb’s measure for robot exposure (y-axis) and Dengler’s measure for routine tasks (x-axis). Although the correlation is not perfect it is relatively strong.

Table C.1 replicates our main results with the routine measure instead of the robot exposure measure. The results are qualitatively very similar.

**Appendix D. Fixed effects estimations and occupational switcher**

As finding random variation for automation exposure is difficult, this study has to rely on panel data estimators, i.e., fixed effects (FE) regressions. However, fixed effects approaches can, under certain conditions, worsen the endogeneity problem and lead to estimates that are even more biased than those of naive OLS regressions. First, fixed effects regressions might underestimate the true effect. In our specific case, occupational switchers might be more capable of dealing with the negative consequences of automation exposure. For example, they might be technologically more versed and motivated because they are younger than the average worker in our sample. If this were the case, our identification variation would stem from a population of compilers with a higher average ability than the average worker in our sample, such that we might underestimate the average effect.

Second, fixed effect regressions might overestimate the true effect. This case would be more severe for the interpretation of our results. Consider, for example, the following simplified version of our main regression model:

$$T_{it} = \delta Robot_{it} + x_{it}\beta + \mu_i + \epsilon_{it} \tag{D.1}$$

where  $T_{it}$  represents the workers’ training participation,  $Robot_{it}$  measures the workers’ automation exposure,  $x_{it}$  measures a set of time-varying observable characteristics,  $\mu_i$  is the time constant unobserved effect on the worker level, and  $\epsilon_{it}$  is the error term. The key identification assumption of a fixed effect approach is  $E(\epsilon_{it}|x_{it}, \mu_i) = 0$ . In our specific application, this assumption might be violated if nonlinear

**Table A.1**  
Baseline characteristics by robot exposure.  
Source: Source: NEPS-SC6 13.0.0, own calculation.

	Robot exposure		Difference
	High	Low	
<i>Training Outcomes</i>			
Training participation	0.24	0.42	0.18***
Number of courses	0.62	1.15	0.53***
Hours in courses	13.19	22.66	9.46***
IT course	0.03	0.11	0.07***
Production courses	0.06	0.07	0.01
Soft & business skills courses	0.06	0.21	0.16***
Other courses	0.15	0.23	0.07***
<i>Individual Characteristics</i>			
Female	0.35	0.56	0.21***
Migration background	0.21	0.11	-0.10***
Education = no vocational degree	0.15	0.06	-0.09***
Vocational degree	0.79	0.60	-0.19***
University degree	0.06	0.35	0.28***
Year of birth	1964.96	1965.34	0.38
<i>Job Characteristics</i>			
Part time employment	0.27	0.35	0.08***
Employed in the public sector	0.19	0.31	-0.12***
Working hours =<15 h	0.09	0.07	-0.02
Between 15 and 30 h	0.12	0.21	0.09***
Between 30 and 40 h	0.31	0.24	-0.07***
Between 40 and 50 h	0.43	0.42	-0.02
> 50 h	0.05	0.07	0.02*
Labor market experience (Years)	20.42	17.95	-2.47***
<i>Firm characteristics</i>			
Industry = agriculture	0.02	0.01	-0.01***
Mining and quarrying	0.01	0.00	-0.00
Manufacturing	0.35	0.19	-0.16***
Energy supply	0.01	0.01	-0.00
Water supply	0.01	0.00	-0.01***
Construction	0.07	0.03	-0.04***
Retail	0.06	0.11	0.04***
Transportation and storage	0.08	0.02	-0.06***
Accommodation	0.02	0.02	-0.00
ICT	0.01	0.06	0.04***
Finances and insurances	0.00	0.06	0.06***
Real estate activities	0.00	0.01	0.01
Prof., scient. and techn. activities	0.02	0.06	0.04***
Administrative services	0.06	0.02	-0.04***
Public admin. and defense	0.04	0.13	0.09***
Education	0.01	0.12	0.11***
Human health and social work	0.17	0.12	-0.05***
Arts, entertain. and recreation	0.01	0.01	-0.01
Other service activities	0.02	0.03	0.00
Households as employers	0.01	0.00	-0.00
Extraterritorial organizations	0.00	0.00	0.00
Firm Size = below 10	0.17	0.20	0.03*
Between 10 and 50	0.31	0.31	-0.00
Between 50 and 200	0.25	0.22	-0.03
Between 200 and 500	0.11	0.11	0.00
More than 500	0.17	0.16	-0.00

This Table shows averages for training outcomes as well as individual, job, and firm characteristics by Webb's (2019) robot-exposure measure. The first column shows averages for workers working in highly exposed occupations. The second column shows averages for workers working in low-exposed occupations. The third column shows the differences (low vs. high) and the significance of a t-test.  
\* $p < 0.1$ ; \*\*\* $p < 0.01$ ;

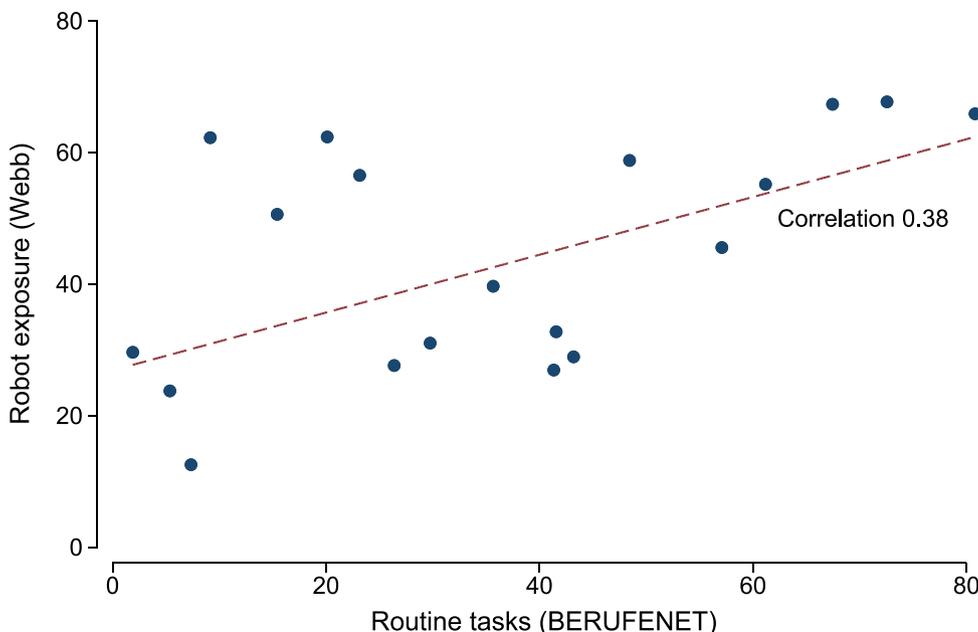
unobserved factors are correlated with both the workers' probability of switching occupations and their training participation.

Let us, for example, consider the following error structure  $\epsilon_{it} = u_{it} + s_i \times \tau_{it}$ , where  $u_{it}$  is normally distributed with zero mean and constant variance.  $s_i$  is a dummy variable indicating whether the worker is a switcher or not, and  $\tau_{it}$  is an unobserved time-dependent component that correlates with  $t$  and  $Robot_{it}$ , e.g.,  $\tau_{it}$  might represent unobserved worker ability leading workers to simultaneously train more and switch out of occupations with high automation exposure.

In this case, both the OLS estimator with  $\hat{\delta}_{OLS} = \delta + \frac{Cov(Robot_{it}, \tau_{it})}{Var(Robot_{it})}$  and the FE estimator  $\hat{\delta}_{FE} = \delta + \frac{Cov(Robot_{it}, \tau_{it})}{Var(Robot_{it})}$  with  $\widetilde{Robot}_{it} = (Robot_{it} - Robot_{it})$  and  $\widetilde{Robot}_{it} = T^{-1} \sum_{t=1}^T Robot_{it}$  are biased because  $Cov(Robot_{it}, \tau_{it}) \neq 0$  and  $Cov(Robot_{it}, \tau_{it}) \neq 0$ . Moreover, the bias might be larger in the fixed

effect regression than in the OLS regression because  $Var(\widetilde{Robot}_{it}) \leq Var(Robot_{it})$ . In principle, the above relationship is a form of the *included variable bias*, as discussed in more detail by DiNardo and Lee (2011).

To further analyze whether an error structure as presented above might indeed bias our estimates Table D.1 presents more details about the identifying variation by presenting descriptive statistics for workers who switch from high- to low-automation-exposed occupations and workers who switch from low- to high-automation-exposed occupations. The results reveal that our sample contains 390 switches out of occupations with a very high automation exposure and 301 switches into these occupations. Given that we have approximately 9000 individuals in the data, the switching incidence may appear small in absolute



**Fig. C.1.** Correlation between robot exposure and routine tasks. The Figure shows the correlation between the share of routine tasks and Webb's (2019) robot exposure measure. The solid line indicates fitted values. Scatterplot is binned. Source: NEPS-SC6 13.0.0, own calculation.

**Table C.1**

Effect of task composition on training participation.

Source: Source: NEPS-SC6 13.0.0, own calculation.

	I	II	III	IV	V
	<i>Panel A: continuous measure</i>				
Share of routine tasks	-0.025*** (0.001)	-0.020*** (0.001)	-0.018*** (0.001)	-0.010*** (0.003)	-0.010*** (0.003)
R <sup>2</sup>	0.024	0.035	0.038	0.018	0.020
	<i>Panel B: dichotomous measure</i>				
High routine intensity	-0.063*** (0.013)	-0.050*** (0.012)	-0.032*** (0.012)	-0.019 (0.027)	-0.026 (0.027)
R <sup>2</sup>	0.010	0.027	0.031	0.017	0.020
Education	No	Yes	Yes	Yes	No
Individual controls	No	No	Yes	Yes	No
Job characteristics	No	No	No	Yes	Yes
Firm characteristics	No	No	No	Yes	Yes
Individual f.e.	No	No	No	No	Yes
Obs.	47350	47350	47350	47350	47350

Dependent variable: training participation (yes/no). Column I show results for an OLS version of Eq. (1) without individual fixed effects and other controls. Column II includes education. Column III includes education and other individual controls (gender, migration background, age). Columns IV and V use individual fixed effects as specified in Eq. (1). Column IV shows results without job and firm characteristics. Column V shows results with job and firm Characteristics. All regressions include time fixed effects. Standard errors in parentheses are clustered on the individual level. \*\*\*p < 0.01.

values. However, as high-automation-exposure occupations constitute only 25 percent of the data, the switching incidence is high in relative terms. Moreover, the fixed effect specifications with the continuous exposure measure rely on more identifying variation.

Comparing workers who switch out of occupations with high automation exposure with those who remain in high exposure occupations reveals that workers who leave occupations with high-automation-exposed are more likely to be female, better educated, and younger. In contrast, those who switch into high-automation-exposed occupations are less educated and older than those who remain in low exposure occupations. Thus, we indeed observe that the workers who leave high-automation-exposed occupation are positively selected, such that  $Cov(\widehat{Robot}_{it}, \tau_{it})$  might indeed be negative. However, if  $Cov(\widehat{Robot}_{it}, \tau_{it}) < 0$  and  $Var(\widehat{Robot}_{it}) \leq Var(\tau_{it})$ , then  $-\hat{\delta}_{FE} \geq -\hat{\delta}_{OLS}$  follows. Instead, our main results reveal that including individual fixed effects pushes the large negative OLS estimate of  $\delta$  closer toward zero, i.e.,  $-\hat{\delta}_{FE} < -\hat{\delta}_{OLS}$ . Although this result does not allow us to assess whether the

fixed effect approach under or still overestimates the true effect, we can at least conclude that the fixed effect approach is more conservative than the OLS approach.

Nevertheless, in the following, we provide three additional robustness checks to support the usage of fixed effects estimation in our main regressions. First, we follow Wooldridge (2010) who proposes to run both FE regressions and first-difference (FD) regressions as a sanity check. The idea is that FE regressions are more efficient when the error terms are serially uncorrelated with the independent variables, while the FD estimates are more efficient if the error terms follow a random walk. As a result, contemporaneous correlation between the independent variables and the error term leads to different probability limits for FE and FD estimators, and we should worry about endogeneity if both estimators differ widely. The first column of Table D.2 shows the results of the FD approach and reveals a coefficient estimate that is very similar to the one in our main FE specification.

**Table D.1**  
Switcher composition.  
Source: Source: NEPS-SC6 12.1.0, own calculation.

	Switcher	Difference to	Switcher	Difference to
	High → Low	High exposure	Low → High	Low exposure
Female	0.536	0.198*** (0.026)	0.558	-0.008 (0.029)
Migrant	0.118	-0.086*** (0.022)	0.136	0.036** (0.018)
Low educated	0.062	-0.081*** (0.018)	0.086	0.034*** (0.013)
Medium educated	0.772	0.044** (0.022)	0.807	0.224*** (0.029)
High educated	0.167	0.125*** (0.013)	0.106	-0.258*** (0.028)
Age	45.200	-1.818*** (0.579)	47.319	1.593** (0.630)
Experience	17.648	-3.897*** (0.667)	19.533	1.176* (0.673)
Large Firm (>200)	0.205	-0.088*** (0.025)	0.203	-0.109*** (0.027)
Observations	390	2607	301	7061

Notes: Columns one and three shows the descriptive characteristics of workers who switch from high (low) to low (high)-automation-exposed occupations. Columns two and four show the respective differences to workers who remain in high (low)-automation-exposed occupations. \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ ; S.

**Table D.2**  
Robustness checks for fixed effects regression.  
Source: Source: NEPS-SC6 12.1.0, own calculation.

	First difference	Lead	Time trend
High robot exposure	-0.068*** (0.022)	-0.051*** (0.019)	-0.064*** (0.022)
Lead		0.019 (0.019)	
R-square	0.021	0.019	0.54
Observations	34667	34667	47350

Dependent variables: Hours spent in training courses, number of courses. All columns show results for a version of Eq. (1) using different dependent variables. Columns I and II show results for the hours spent in training as the dependent variable. Columns III and IV show results for the number of courses as the dependent variable. Columns I and III show results for the extensive margin, i.e., unconditional on training participation. Columns II and IV show results for the intensive margin, i.e., conditional on training participation. All regressions include individual fixed effects and time fixed effects. Standard errors in parentheses are clustered on the individual level. \*\*\*  $p < 0.01$ .

Second, Wooldridge (2010) proposes testing for strict exogeneity in FE estimators by adding a lead of the independent variable to the regression. Under strict exogeneity, the lead should not be significantly different from zero. The second column of Table D.2 shows an insignificant lead of  $Robot_{it}$ , suggesting that the training intensity only changed in response to the occupational switch and not before the switch. Third, we directly model the potentially unobserved trend by interacting the individual fixed effect with a linear time trend. Again, the results change only marginally. Overall, our results suggest that the FE estimates are more conservative than OLS and FD because they lead to a smaller negative effect.

**Appendix E. Survey questions on individual and general firm support for training investments**

The NEPS provides detailed information about their firms’ financial and nonfinancial training support for workers. One set of questions addresses firms’ general support for training participation in terms of human resource practices. The survey questions are as follows:

- Does your company have a shop agreement governing continuing education?
- Is there continuing education planning on a regular basis for the employees there?
- Does your company finance or provide classes or training courses?

- Is there a staff member, unit or department responsible for training or continuing education?

Another set of questions addresses the firms’ individual support for further training. The detailed survey questions are as follows:

- Has your current employer offered to release you from work to attend training sessions and courses?
- Has your current employer offered to pay for you to attend courses and training sessions, given you aid or provided other kinds of financial support?

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