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Evolving work, evolving skills: how different forms of further training are used to adapt to technological change depending on task complexity

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ABSTRACT

Technological transformation is changing the tasks and skill profiles of the workforce in modern Western societies, and participation in further training is often seen as an adaptation strategy. However, the specific types of training used to address the increasing task complexity and technology use remain unclear. This study examines the impact of technology use at work on participation in informal and non-formal further training in Germany, considering the complexity of job tasks. Using data from the German National Educational Panel Study (NEPS), logistic regression models show that a more frequent use of networked digital technology tends to favour participation in informal training while for non-formal training the effect is smaller and insignificant. The expected interaction between technology use and task complexity on participation in non-formal and informal training is not significant. Further analysis suggests that the underlying mechanisms may be more complex and vary by age and sector. Overall, the findings provide initial evidence that non-formal and informal training appear to play different roles in the process of technological change, although further research is needed to validate and understand the underlying dynamics.

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KEYWORDS

Further training; technology; task complexity; individual level

Introduction

Looking at the world of work, transformation processes, in particular technological innovation, are changing the work and skill requirements of employees, especially in modern Western societies. In Germany, technological change has led to fundamental structural change of the labour market (Arntz, Gregory, and Zierahn 2019), as it has contributed to a reallocation of jobs from the manufacturing sector at the core of the economy to the service sector (Hutschenreiter, Santini, and Vella 2021), accompanied by a shift towards more complex tasks (Latos et al. 2018). In line with this, Germany has

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experienced skill upgrading rather than widespread technology-related unemployment in the wake of technological change, with net employment growth since the 1990s occurring in the highest wage and skill groups (Oesch and Piccitto 2019; Oesch and Rodriguez Menes 2011). Such labour market transformation processes often go hand in hand with the emergence of new work requirements and changing job profiles (Wegerif 2002), which can lead to technology-induced ‘skills obsolescence’ (Grip and van Loo 2002), i.e. the process by which employees’ skills become obsolete or less valuable over time. As a consequence, relevant skills need to be continuously specified, updated and extended (Helmrich and Leppelmeier 2020), and job-relevant skills acquired at the beginning of the educational career (e.g. through school education or initial vocational training) are no longer sufficient to meet the work demands of a whole working life.

Against this background, a growing number of voices, not only in Germany, are pointing to the need for a change in the culture of learning – from the one-off acquisition of school and vocational skills to lifelong learning (e.g. Blossfeld and von Maurice 2019). Empirical support for this argument can be found in the increasing demand for further training by companies and individuals in Germany in recent years as a result of technological transformation processes (Beer and Mulder 2020; Lukowski, Baum, and Mohr 2021).

As technological change leads to skills obsolescence and has mainly driven upskilling and a shift towards more complex tasks in Germany, we argue that the joint consideration of technology use and task complexity is essential for understanding training patterns in the context of these transformation processes. Thus, this paper examines the impact of technology use in the workplace on participation in different forms of further training under the influence of task complexity (see Figure 1). We assume that the use of technology in the workplace leads to an increased need for further training. In parallel, we argue that employees perform tasks of different complexity and that task demands change differently due to technological change. Therefore, we expect them to participate in different forms of training as an adaptation strategy.

We employ empirical-quantitative analyses to investigate two research questions:

- (1) Does technology use influence the likelihood of participating in non-formal and informal further training?

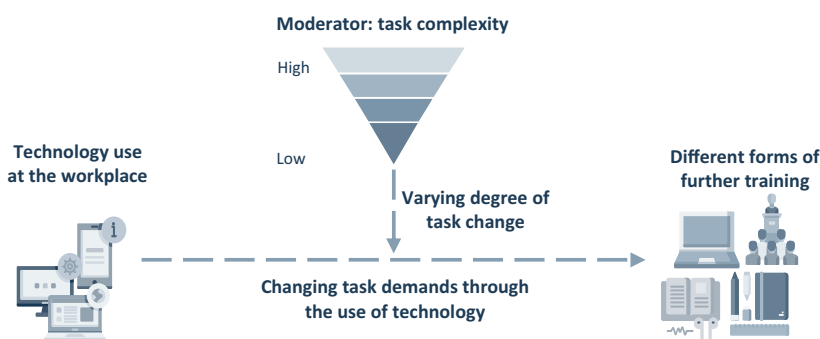


Figure 1. Hypothetical chain of effects of technology use in the workplace via task complexity to further training needs. Source: own illustration, Icons used by <https://slidesgo.com>.

- (2) To what extent does the task complexity moderate the impact of technology use on the likelihood of non- and informal further training?

With this novel approach, we address a research gap by analysing the combined influence of job tasks and technology use on training participation, whereas previous research has examined these factors separately. By integrating theoretical perspectives on technological task change and further training, the study provides new insights into the likelihood of participating in different forms of training in response to technological change. The results can improve the understanding of selection mechanisms and training decisions in this context, identify disadvantaged groups and derive implications for policy measures as well as individual and firm training strategies.

Theoretical approach

The impact of technology use on work and skill requirements

To identify the potential for task change through technology, many studies use the task-based approach (TBA, Autor, Levy, and Murnane 2003). The core idea is that jobs are seen as bundles of tasks, which can be routine or non-routine, and cognitive or manual. It is argued that technological progress primarily affects routine, repetitive and rule-based tasks, leading to their automation and displacement, while non-routine tasks tend to be more complex, making them less amenable to automation (routine-biased technological change (RBTC)). Related to this, the skill-biased technological change (SBTC) hypothesis explains how technological progress affects the demand for different types of skills, and suggests that technological progress disproportionately benefits employees with higher skill levels. This leads to an increased demand for skilled employees, such as those with higher education and technical skills, while reducing the demand for unskilled or low-skilled employees (e.g. Goldin and Katz 2008). In general, TBA, RBTC and SBTC are formulated to examine the extent to which (future) economic effects result from increased technology use (Autor and Dorn 2013; Fernández-Macías and Hurley 2017; Goos, Manning, and Salomons 2014).

Applied to Germany, the digital transformation of existing jobs and their tasks is more pronounced than their displacement (Arntz, Gregory, and Zierahn 2019; Diewald, Björn, and Eva 2020; Helmrich et al. 2016). Employees' task profiles tend to change towards more complex tasks that require advanced problem-solving skills, flexibility, creativity, intuition and complex communication and management skills (Bachmann and Cim 2018; Bonin, Gregory, and Zierahn 2015; Latos et al. 2018). A trend towards deskilling, which tends to focus on the deskilling of medium-skilled employees, is comparatively low in Germany and mainly affects low-skilled employees who face increased pressure to adapt to technological change (Arnold et al. 2016). Trends towards digital Taylorism, i.e. the increasing digital optimisation and control of work processes, can only be identified for certain task areas. While discretion in service tasks tends to be restricted by the use of technology, knowledge-related and manufacturing tasks in particular benefit from the more frequent use of technology in the sense of digital self-determination (Kirchner, Meyer, and Tisch 2023).

Overall, technological change in Germany has led to a growing demand for highly skilled employees, such as IT specialists (Helmrich et al. 2016). And IT-related professional jobs with non-routine analytic tasks, which often involve highly complex work requirements, benefit most from technological progress (Genz et al. 2021).

Further training as a strategy for adapting to technology use

For the German training system, a tripartite distinction between formal, non-formal and informal further training has been established, which is also reflected in the empirical data collection. According to the Classification of Learning Activities (CLA, Eurostat 2016), we define non-formal training as organised and intentional, typically taking place in commercial or company-sponsored courses with supervised learning processes. Although it does not lead to formal qualifications, participants may receive certificates of attendance. Informal training, on the other hand, is more self-organised and takes place outside formally organised and supervised courses and does not lead to formal qualifications. Examples include reading professional literature, using digital learning programmes or sharing experiences with colleagues (Eisermann, Janik, and Kruppe 2014, 478). In the following, we focus on informal and non-formal training because these are the two dominant forms of further training in Germany (Authors' Group on Educational Reporting 2020, 215f.). Formal training is therefore not part of the analysis.

In terms of the functions of training, non-formal training helps to build broader, generic, decontextualised knowledge that encourages critical reflection, challenges existing understandings and is applicable to other contexts (Rogers 2014, 64). In contrast, informal training is more contextual and task-oriented, focusing on concrete applications. It increases the relevance of general (formalised) training by applying standardised concepts to specific situations (63f.). Thus, we argue that non-formal and informal training have different functions in adapting to transformation processes in the workplace, not only in the context of technological change.

Most existing research has examined the influence of job tasks and technology use on training participation separately. At the employee level, there is a positive relationship between technology use and the likelihood and/or duration of informal (e.g. Krekel and Hall 2008; Kuper and Kaufmann 2010) and non-formal training (e.g. Schindler, Weiss, and Hubert 2011). Studies by O'Connell and Byrne (2012) and Janssen et al. (2018) indicate that investment in and adaptation to new technologies increase the likelihood of employees participating in company-funded non-formal training. Conversely, research by Heß, Janssen, and Leber (2023) reveals that employees in occupations with high exposure to robot technology receive significantly less training.

Looking at the relationship between further training and task complexity, recent studies for Germany confirm that participation in non-formal training at the workplace depends on job tasks. Several studies show that employees performing complex analytic and interactive non-routine tasks are more likely to participate in further training than other employees, and some of the studies indicate that routine tasks have a negative impact on this likelihood (Ehlert 2020; Görlitz and Tamm 2016; Kleinert and Wölfel 2018; Mohr, Troltsch, and Gerhards 2016; Zeyer-GlioZZo 2023).¹

Research on the combined effects of technology use, task complexity, and training participation is limited. Mohr, Troltsch, and Gerhards (2016) found that employees performing complex non-routine tasks are more likely to participate in company-funded training, especially with frequent technology use and minimal repetitive tasks. However, their study focused only on low-skilled employees at the firm level, limiting its broader applicability. This paper addresses this gap by examining these factors at the individual level, across all skill levels, and differentiating between non-formal and informal training participation.

Research model

Based on existing research, we expect a positive relationship between the use of digital technologies in the workplace and employees' participation in informal and non-formal training. In addition, we propose that the relationship between workplace technology use and the likelihood of training varies with task complexity (see Figure 2).

According to the SBTC model and the TBA, technological progress is associated with shifts in skill demand, often favouring workers with higher skills and more complex tasks. Conversely, employees with lower skill levels and less complex tasks may be under greater pressure to adapt to technological change by acquiring new knowledge that enables them to take on tasks that are less susceptible to automation. Building on the distinct functions of non-formal and informal training, we suggest that employees with highly complex tasks are more likely to participate in informal training when using digital technologies, as such training primarily helps to refine and update existing knowledge. This should be particularly important for task-oriented use of technology in the concrete work context. In contrast, employees with less complex tasks may be more likely to participate in non-formal training when using digital technologies, as this type of training introduces new and specific concepts and skills that broaden the knowledge base to take on new tasks. These considerations lead to the following hypotheses:

H1: The more intensive the use of digital technologies, the higher the likelihood of participation in informal and non-formal further training.

H2: The more intensive the use of digital technologies and the lower the complexity of tasks, the higher the probability of participating in non-formal further training.

H3: The more intensive the use of digital technologies and the higher the complexity of tasks, the higher the probability of participating in informal further training.

Data and method

Data

We used data from the German National Education Panel Study (NEPS), starting cohort adults (SC6: 13.0.0, Blossfeld and von Maurice 2019; NEPS Network 2022). The NEPS Adult Cohort aims to collect data on lifelong learning, adults' educational, employment and

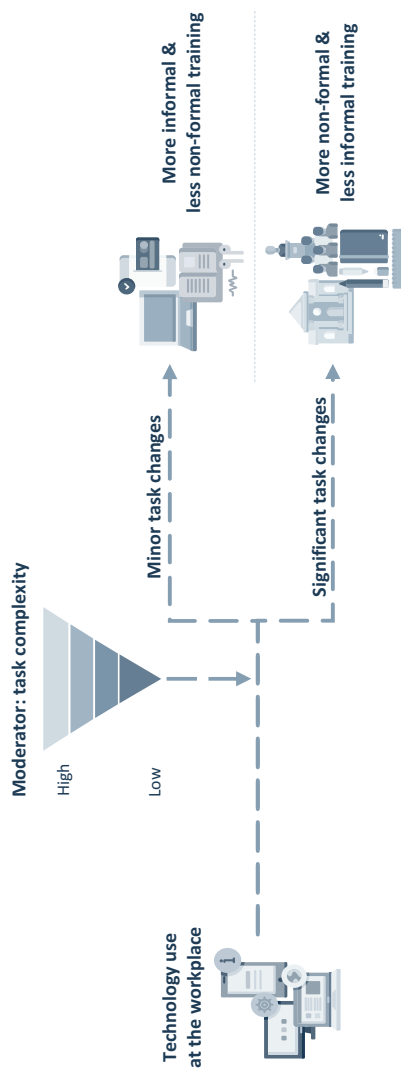


Figure 2. Influence of technology use on participation in non-formal and informal further training, moderated by work complexity. Source: own illustration, Icons used by <https://slidesgo.com>.

family histories, and their skill development. The population comprises working-age adults (the 2009 starting population includes persons born between 1944 and 1986) living in Germany (Allmendinger et al. 2019). As of now, there are 12 NEPS waves (1st wave 2009/2010). Since we used a new instrument for measuring the technology use at the workplace (Friedrich et al. 2022) that was included in wave 11 and measured the influence of this on participation in further training in the following year, we considered waves 11 and 12 (thus training participation between 2019/2020 and 2020/2021). In the following, we only considered employees (excluding the self-employed) aged 60 or less ($N = 6,690$; 3,593 individuals).

The data contains missing values due to item and wave non-response. Since complete case analyses often lead to inefficient analyses and bias in the case of missing values, and analyses with multiple imputations yield better results (Donders et al. 2006), we imputed these by chained random forests using the package *missRanger* in R (R Core Team 2022; Meyer 2021). We used *missRanger*, as some authors recommended using tree-based methods for imputation over, e.g. predictive mean matching in *mice* (Akande, Li, and Reiter 2017; Murray 2018), especially when the data structure is more complex, such as with interaction effects (Doove, van Buuren, and Dusseldorp 2014) or panel data (Schwerter et al. 2024), as we both have here. Detailed information on the missingness pattern and implementation of the imputation can be found in the appendix in Section A.

Further training

As described above, non-formal training comprises courses, often organised commercially or by companies, that do not lead to recognised degrees. Here, we only considered non-formal training courses that have been conducted for professional or professional and private reasons. For a small number of courses, this information is not available. However, we assume by the fact that they were indicated in the context of questions on vocational education, that these courses also have an occupational purpose. We created a binary variable indicating participation in training between wave 11 and wave 12 (1 participation, 0 no participation).

For informal training, we considered four different types of learning: attending lectures, attending conferences, learning with digital media (online or with apps, e.g. wikis, forums, podcasts or YouTube), and learning with media (computer, learning CDs or DVDs or similar). Again, we only considered activities that were at least partially carried out for professional reasons. The informal training variable was generated by taking the value 1 at wave 12 if at least one of the four informal learning activities had been attended since the last interview, and 0 otherwise.²

Technology use at the workplace

For technology use at the workplace, we relied on a newly developed battery of items about the use of networked digital technologies in the job, e.g. ICT (Friedrich et al. 2022),³ including using the internet or intranet to search for information, creating or editing digital files, exchanging files with other people, maintaining websites, creating websites, and programming algorithms for intelligent systems. There is information about whether the respective activities are carried out at all and how often. Thus, we created variables with a value range from 0 (never) to 5 (several times a day). We used a polychorical factor analysis (Kolenikov and Angeles 2004) to combine this categorical information and form

Table 1. Training participation, technology use and complexity.

Variable	Mean	SD	Range/Values	N
Non-formal training	0.28	0.45	0/1	3,063
Informal training	0.33	0.47	0/1	3,061
Technology use	0.39	0.22	0–1	3,323
Complexity	0.56	0.19	0–1	3,322

Source: NEPS SC6: 13.0.0, wave 12 (further training) and wave 11 (remaining variables), without imputations.

an index ranging from 0 to 1 with values close to 1 indicating a more technical job and values close to 0 indicating a job with little or no use of digital technologies.

Task complexity

To measure task complexity, we used the instrument developed by Matthes et al. (2014) to measure job tasks according to the TBA. The task dimensions surveyed include analytic, interactive, manual, autonomous and (non-)routine tasks. Complexity here represents an inverse instrument for measuring routine tasks, i.e. tasks that are difficult to automate. The following activities are part of this dimension: solving difficult problems, learning new things, getting acquainted with assigned tasks, reacting to unanticipated situations, changing work-assignments, and performing new tasks. For each of these tasks, respondents were asked to indicate how often they performed them on the job (from always or very often (1) to very rarely or never (5)). The items were used to form an additive index according to the procedure of Matthes et al. (2014, 283). Accordingly, values close to 1 indicate a job with a high intensity in complex tasks and close to 0 denotes a job with a low intensity in complex tasks. Table 1 shows the training rate, distribution of technology utilisation and task complexity in our sample.

Method

For our analyses, we estimated logistic regression models:⁴

$$P(y_i|t_i, c_i, \mathbf{x}_i) = \frac{\exp(\beta t_i + \gamma c_i + \mathbf{x}_i' \delta)}{1 + \exp(\beta t_i + \gamma c_i + \mathbf{x}_i' \delta)}$$

Here, the probability of a person i to have participated in at least one non-formal or informal learning activity since the last interview ($y = 1$) is supposed to depend on the use of digital technologies in the workplace t , the task complexity c , and a vector $\mathbf{x}$ of control variables. β , γ and the vector δ are the parameters to be estimated.

The control variables consist of factors related to both training participation and technology use or task complexity. For example, high-skilled employees tend to have a higher probability of technology use at work, e.g. computers (Riddell and Song 2017), and of training participation (e.g. OECD 2019) than low-skilled employees. Hence, without controlling for education, the coefficient of technology use would be biased upwards, as a positive effect would at least partly reflect educational training difference. The other job tasks are also associated with different levels of training participation and technology use, for example higher levels of analytic non-routine tasks with higher training rates (Görlitz

and Tamm 2016) and with more computer use due to complementarity (Autor, Levy, and Murnane 2003). Furthermore, we included age, gender, children interacted with gender, occupation, sector, company size, work experience in the respective occupation and work scope in our model. For a discussion of the relationship between these variables and training participation, see Zeyer-Gliozzo (2023), and job tasks and technology utilisation, see Seegers and Ehmann (2021).

Additionally, for weighting, we followed a model-based approach and included all design variables and all variables used to calculate the non-response-adjusted weights in our model (Würbach et al. 2021, 46f.). These are household size, federal state, marital status, contact attempts and BIK-10 Region size. For an overview of the measurement and distribution of the respective variables, see Table B-1 in the appendix.⁵

To avoid problems of reverse causality, which are plausible due to bidirectional links between training and job tasks (Zeyer-Gliozzo 2023), the probability of training participation (between wave 11 and 12) is modelled with information on explanatory variables measured beforehand (wave 11).

To analyse whether the effects of technology use vary with the degree of task complexity, interaction effects between these variables were included. Note, however, that the logit coefficient of the interaction in logistic regressions can be misleading, as it may differ in sign, size or significance compared to the actual interaction effect with respect to the metric under consideration, i.e. the probability (of training participation) (Ai and Norton 2003; Mize 2019). Therefore, following Mize (2019), we presented the interactions by plotting the average marginal effects of technology use on the training probability for different values of task complexity.⁶

Results

First descriptive analyses show, as expected, that employees with higher technology use also have higher participation rates in non-formal and informal further training (Appendix, Figure C.1-1). For instance, 17% of employees who rarely use digital technologies (< first quartile) participated in non-formal and 15% in informal training in the past year (average: 28% and 33%, Table 1). In contrast, 34% of frequent users ($\geq$ third quartile) took part in non-formal training and 47% in informal training, indicating substantial differences, which are more pronounced for informal training. Furthermore, as theoretically argued, there is a positive relationship between technology use and the complexity of work, i.e. the more technology is used, the more complex tasks an employee performs. When looking at the different elements of technology use (e.g. searching for information or editing files), it can be seen that it is more the frequency and less the type of use that varies between employees with different levels of complexity (Appendix, section C.2). Finally, in the data, a positive association exists between participation in non-formal further training and technology use for employees with low task complexity (first quartile), while the association is more irregular for employees with higher task complexity (Appendix, Figure C.3-1). The share of employees with informal further training is in most cases higher when technology is used more frequently, regardless of task complexity. However, the link gets stronger for employees with more complex tasks.

The results of our multiple logistic regressions analysing the impact of technology use on training participation are presented in Table 2 (see Appendix Table D-1 model 1 and

Table 2. Technology use, task complexity and participation in further training.

Model	Non-formal training		Informal training	
	Logit	AME	Logit	AME
Technology use (centred)	0.554 (0.360)	0.100 (0.065)	0.966* (0.374)	0.183** (0.070)
Complexity (centred)	1.063** (0.393)	0.193** (0.068)	0.677+ (0.360)	0.128+ (0.067)
N	3,386	3,386	3,386	3,386

Source: NEPS SC6: 13.0.0, wave 11 and 12. Note: Logistic regressions (logit-coefficients). Standard errors in parentheses. We control for the control variables mentioned in the data section above. Significance Level: +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.

model 3 for the full models including the coefficients of all control variables). In line with our hypothesis H1, a positive relationship between technology use and the likelihood of informal and non-formal training emerges. However, the link is larger and significant only for informal training. On average, a one standard deviation (SD) increase in the use of digital technologies is associated with a 4% points (0.22×0.183) higher probability of participation in informal training. In addition, more task complexity is also positively related to the training probability. The relationship is stronger (with an average marginal effect (AME) of 4% points per SD) and highly significant for non-formal training, while the link to informal training is somewhat smaller (AME of 2% points per SD, $p < 0.1$).

Figure 3 and Figure 4 show the results of the models with interactions of the two factors (see Appendix Table D-1, models 2 and 4 for the full models). Figure 3 presents the AME of technology use together with the 90%, 95% and 99% confidence intervals for different levels of complex tasks intensity. Wald-tests are used to determine whether differences between the AME are significant (Mize 2019). For ease of interpretation, Figure 4 presents the predicted probabilities of training participation at different levels of technology use and complexity.⁷ We find a positive AME of technology use on the probability of participating in non-formal training for employees with below-average task complexity (mostly weakly significant, left panel in Figure 3). The more complex tasks are performed, the smaller this relationship becomes, up to a slightly negative AME. Similarly, the left panel of Figure 4 shows that employees performing few complex tasks (−2SD) are 8% points less likely to attend non-formal training when technology use is low (−1SD, 15%) than when technology use is high (+1SD, 23%). Employees with above-average task complexity (+2SD) have a consistently higher likelihood of training (due to the correlation with complexity), but there is little difference between low (35%) and high (34%) technology use. However, Wald-tests indicate that the differences between the AME of technology use according to varying levels of complexity are not significant. Therefore, the results are subject to uncertainty and hypothesis H2 cannot be confirmed.

Informal training, as expected, shows the opposite trend, i.e. a higher training probability in jobs with more technology use and more complex tasks. Thus, the AME of using digital technologies on informal training participation increases with task complexity (Figure 3, right panel). For employees with few complex tasks (−2SD), the difference in the probability of further training between low (−1SD) and high technology use (+1SD) is 4% points, compared to 14 points for those with many complex tasks (+2SD) (Figure 4, right panel). Again, however, Wald-tests show no significant differences between the AME, so the results cannot be generalised, and our hypothesis (H3) cannot be confirmed.

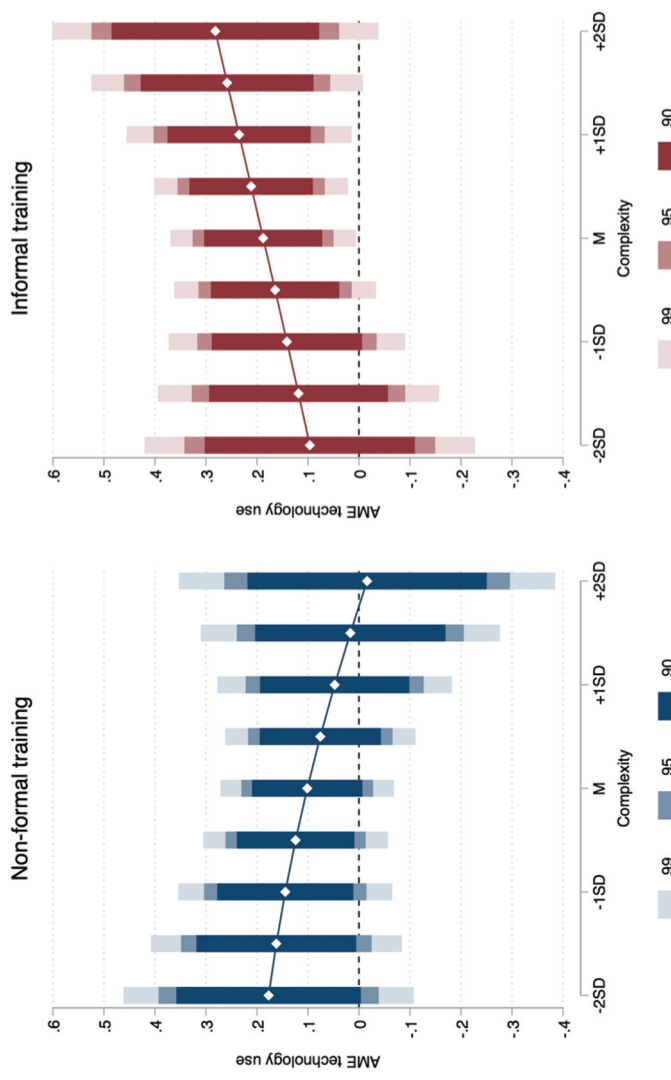


Figure 3. Average marginal effects (AME) of technology use on the probability of training depending on the complexity of tasks. Source: NEPS SC6: 13.0.0, wave 11 and 12. Note: Logistic regressions, average marginal effects with 90, 95 and 99% confidence intervals. We control for the control variables mentioned in the data section above.

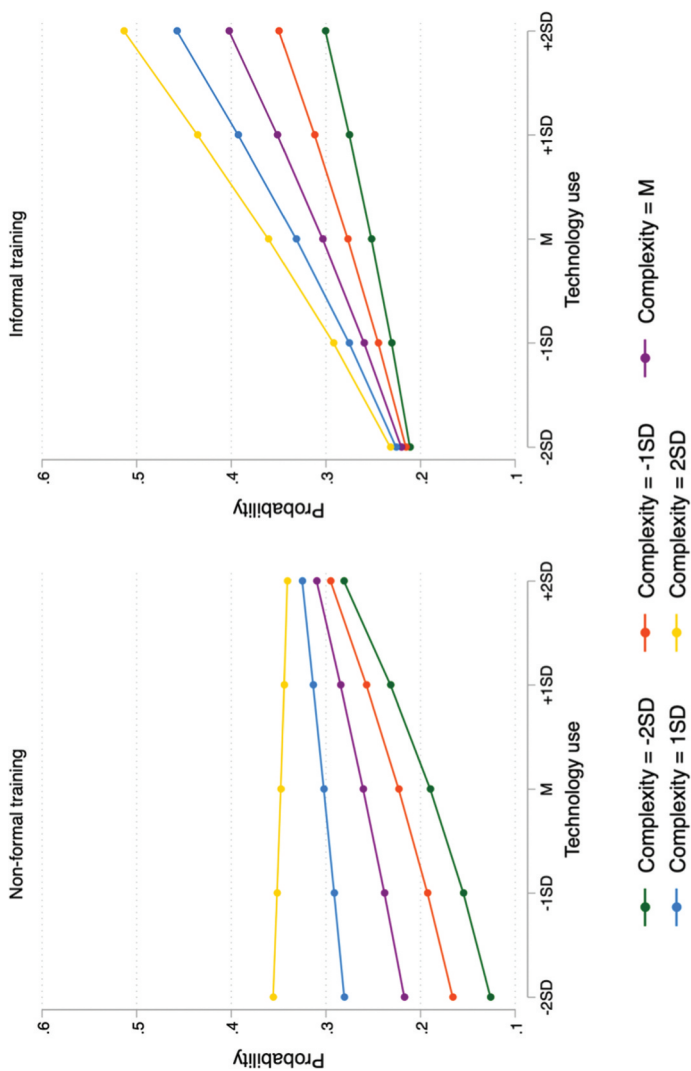


Figure 4. Average marginal effects (AME) of technology use on the probability of training depending on the complexity of tasks (complete case analysis). Source: NEPS SC6: 13.0.0, wave 11 and 12, without imputations. Note: Logistic regressions, average marginal effects with 90, 95 and 99% confidence intervals. We control for the control variables mentioned in the data section above.

Finally, if we look at the differences in the probability of further training depending on the level of complexity for different levels of technology use, we see another interesting pattern (Figure 4): the probability of participation in non-formal further training among employees at different levels of complexity converges with increasing technology use. At the same time, the probability of participation in informal further training diverges between the levels of complexity with increasing technology use.

Robustness checks

We have tested the sensitivity of our results to the imputation method and operationalisation used: With regard to the imputation method, we calculated the results using complete case analysis without imputation, given that there is some debate as to whether multiple imputation consistently performs better for different missing data mechanisms (e.g. Pepinsky 2018) (see also the discussion in Appendix A). Figure E.1–1 in the Appendix shows the AME of technology use by complexity, with very similar patterns to our main analysis (see additionally Table E.1–1 in the Appendix for results of our main model without interactions). The differences between the AME are somewhat more pronounced for non-formal training, while they are slightly smaller for informal training (still not significant in either case). Additionally, we used a different imputation method, i.e. we imputed missing values using multivariate imputation by chained equations (*mice*) (van Buuren and Groothuis-Oudshoorn 2011). For implementation, we used *mice* with predictive mean matching and included the interaction variables in the imputation model according to van Buuren (2018, Ch. 6.4.2). The results (see Appendix, Table E.1–2 and Figure E.1–2) are somewhat more pronounced than in our main models, although still without significant differences in the AME, and support our findings.

In checking how robust our results are to the operationalisation used, we looked at the indexing of technology use. For comparison, we calculated the index as a simple sum index instead of the polychorical factor analysis used in our main model. The results (see Appendix, Table E.2–1 and Figure E.2–1) differ only slightly and support our conclusions.

Additional analyses

Are there differences according to the type of informal training?

Instead of looking at informal training in general, we also estimated models for all four different forms of informal training individually. This is helpful because the measurements of informal learning vary widely across studies, making it difficult to interpret and compare the results. Moreover, in contrast to non-formal training, job-related informal training in NEPS comprises only four different forms of learning, making an overall variable less generalisable and separate analyses easier to implement. By doing so, technology use has a significant positive effect on attending lectures and learning with digital media (Appendix Table F.2–1). In addition, with attending lectures the same trend emerges as with informal further training in general, namely a higher AME of technology use with increasing complexity, although the differences are not significant here either. For the other forms of informal training, especially learning with (digital) media, the interplay between technology use and complexity is less pronounced (Appendix Figure F.2–1).

Are there differences by age and sector?

We also calculated our models separately for age and sector groups to account for employee heterogeneity.⁸ Age could play a role, since different age groups may have different needs for skill adjustments in the context of technology use (due to younger people's greater familiarity with digital technologies). There may also be differences between sectors, since we are specifically dealing with the use of ICT (and not, for example, the use of machinery), which could play a different role for participation in training in different industries.

With regard to age, employees aged 55 or above show the greatest AME of technology use on the likelihood of participating in informal training, while for those aged between 45 and 54 it is closer to 0 and not significant (Appendix Tables F.2–1 and F.2–2). Additionally, despite still insignificant differences in the AME of technology use on training participation by complexity, our data reveal distinct patterns regarding the interplay between both factors. For younger employees, complexity seems to be more relevant for the correlation between technology use and non-formal training (with a mitigating effect), while for older employees it is more important when it comes to informal training (with a reinforcing effect) (Appendix Figure F.2–1). In terms of sectors (Appendix Tables F.2–3 and F.2–4 and Figure F.2–2), the AME of technology use on informal training is largest in economic services, while it is much smaller in public and personal services ($p < 0.1$) and in manufacturing (not significant). Furthermore, the interactions for employees in economic services show similar patterns to our main findings. However, for manufacturing, the effect of complexity on the relationship between technology use and non-formal training is reversed, i.e. the more complex tasks performed, the stronger the AME.

Mediation instead of moderation?

We theorised that higher technology use is not only related to training participation but also to higher task complexity, which in turn has been shown to correlate with training participation. Therefore, we conducted mediation analyses in addition to moderation analyses to decompose the total effect of technology use on the training probability into an indirect effect mediated by complexity and a direct effect (Breen, Karlson, and Holm 2013). We used the khb method (Karlson, Holm, and Breen 2012), because the coefficients of two nested logistic regression models are not directly comparable. This allows us to assess differences in the coefficients that are solely due to confounding (see Appendix F.3 for more details). The results show that mediation exists for both non-formal and informal training, indicating that part of the total effect of technology use on training participation is mediated by complexity. Nevertheless, there remains a significant ($p < 0.05$) direct effect of technology use on participation in informal training.

Discussion

This study aimed to investigate the relationship between technology use and the probability of participating in non-formal and informal further training, depending on task complexity. Analyses based on German NEPS data show that a more frequent use of networked digital technology tends to favour participation in informal training while for non-formal training the effect is smaller and not significant (partially supporting H1). In parallel, a more intensive performance of complex tasks is linked to a higher likelihood of participation in non-formal and – to a lesser extent – informal training. Thus, the results

indicate that task complexity is an important driver of participation in non-formal training and that the use of technology is a more influential driver of participation in informal training than task complexity. Concerning the interplay between technology use and task complexity, we hypothesised that employees with less complex tasks are more likely to participate in formalised training, like non-formal training (H2), and employees with high task complexity are more likely to participate in self-directed informal training due to higher technology use (H3). Although we can find the hypothesised trends, Wald-tests show that these differences are not significant, leading to a rejection of both hypotheses. These results are robust to different approaches in dealing with missing values or the indexing of technology use.

Regarding limitations, the study focuses solely on digitally networked technologies like ICT, potentially overlooking technologies in the primary and secondary sectors (e.g. machines/plants). Additionally, job-related informal training in NEPS is restricted to four learning types, excluding others such as learning from colleagues or learning by doing. Given the increasing frequency of job and sector changes (Arntz, Gregory, and Zierahn 2019), future research should also explore the role of formal training, like retraining for new jobs in different sectors. However, this is somewhat difficult due to the small number of people participating in formal training (Authors' Group on Educational Reporting 2020). Moreover, this study does not analyse the specific skills imparted by training and whether these enable people to use technology better and/or cope with more complex tasks. Further research should investigate the content, scope, and returns of training to disentangle the different effects.

Despite its limitations, this analysis offers valuable insights into the interplay between technology use, task complexity, and participation in further training. The study found that increased technology use affects non-formal training mainly by impacting task complexity. Only employees with less complex tasks show a significant direct link between technology use and training participation, though this relationship is not significantly different from those with higher task complexity. This contrasts with Mohr, Troltsch, and Gerhards (2016), likely because they focused on low-skilled employees. For informal training, technology use boosts participation across all complexity levels, with more pronounced effects at higher task complexities. While the differences between low and high complexity are not trivial in size, they are also not statistically significant, and interactions between technology use and task complexity remain inconclusive.

One possible reason may be the theoretical approach chosen. We argued that the relationship between technology use and training participation depends on task complexity, as it shapes how technology affects job demands. Specifically, employees with low task complexity should engage in non-formal training to acquire new skills, while those with high task complexity should rely on informal training to refine and update existing knowledge. However, factors beyond changing demands may also play a role. Given that job autonomy enhances performance in complex jobs and correlates with skill level (Lopes, Calapez, and Lopes 2017), employees in high-complex occupations likely have more autonomy, enabling self-directed, informal learning (e.g. in managerial roles). In contrast, employees in less complex jobs with less autonomy may be required to undertake non-formal training. This suggests alternative mechanisms and underscores job autonomy's role in shaping the link between technology use and training participation, warranting further investigation.

In addition, the relationship may be more complex and influenced by the initial level of technology use and vary by age or sector. Additional analysis shows that the effect of technology use and its interaction with task complexity and participation in training varies by age and sector (despite still insignificant differences in the AME). Differences by age could be due to higher average technology use and familiarity of youngers, reducing their need for training in this context. This is in line with the CEDEFOP (2022) study, which found that older people (> 44 years) are less likely to use digital technologies than those aged 35–44, but at the same time are equally likely to upgrade their digital skills (and both groups are less likely to do so than younger people). The low level of use among older people could therefore be interpreted as requiring a greater adjustment of skills.

Finally, the period of analysis, which covers the early stages of the COVID-19 pandemic, may have influenced the results. Studies using NEPS data show that participation in non-formal training and certain informal learning activities, such as attending events (congresses and lectures), declined, while digital learning remained stable. In addition, the impact of education and occupational status on participation in non-formal learning declined, although this was only evident for event-based informal learning (Kleinert and Zoch 2023). This suggests that task complexity may have played a smaller role in training participation over this period, as well as in the relationship between technology use and training participation. Furthermore, the non-significant effect of technology use on non-formal training could be explained by the fact that ICT mainly facilitates digital learning, whereas non-formal training was more affected by pandemic-related cancellations. Accordingly, further analysis with more recent data after the COVID-19 pandemic is desirable to explore the relationships presented.

Our theoretical and empirical analysis underlines that simply advocating more training in response to technological change is insufficient. Instead, the focus should be on holistic training strategies that are tailored to the needs of employees and consider the complexity of tasks and the digitalisation of the workplace. Further research is needed to identify which types of training are effective in developing specific skills and how they prepare employees for the ongoing digital transformation. Encouragingly, employees in less complex roles are increasingly engaged in non-formal and informal training as the use of technology in the workplace expands. In the context of labour shortages and technological advances in Germany, this trend suggests that companies are investing in upskilling their existing workforce due to limited availability of new employees. However, workers in less complex roles who are not exposed to new technologies may be disadvantaged and require targeted interventions. Limited access to technology and fewer training opportunities could hinder their integration into a digitalised workforce and limit their career development. Addressing these inequalities through inclusive training policies will be crucial to ensure that workers, regardless of job complexity, can adapt to and benefit from technological change.

Notes

1. Zeyer-GlioZZo (2023) confirms the findings for both non-formal and informal training, but the association with non-formal training is not always statistically significant.
2. The last interview was on average 12 months ago (mean = 12, sd = 2, min = 7, max = 19).
3. For the sake of simplicity, we will shorten the term to use of digital technologies or technology use in the following.
4. The analyses were conducted using Stata 17 MP. (StataCorp 2021)

5. In order to check for possible problems due to multicollinearity, we calculated the correlations between all variables on the one hand and the variance inflation factor for all variables using a linear probability model on the other. Both results indicate that multicollinearity does not play a role here.
6. We generate average marginal effects plots considering multiple imputations with the user-written programs `mimrgns` and `coefplot` in Stata (Klein 2014; Jann 2014).
7. Note that there is some debate as to whether the pooling of predicted probabilities at fixed values qualifies for pooling under Rubin's rules, so these results should be taken with some caution (Williams 2024). Nevertheless, they show the magnitude of the differences. Figure E.1–1 in the appendix shows similar results without imputations.
8. Due to smaller sample sizes within the groups, some control variables had to be adjusted (e.g. instead of federal state East/West Germany).

Note

The authors declare that they have used Chat GPT 4o and DeepL Write Pro to improve the language and readability of the paper. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Data availability statement

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