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# Continuous vocational education and training and new technologies: on the importance of educational level and technology in the workplace

Andreas Stöckl[1*] and Olaf Struck[1]

**Abstract**

Continuing vocational education and training (CVET) can support technical and digital developments. At the same time, company-based training increases employability in the face of technical rationalization. Multiple studies show that the highly qualified undertake further training more often than the less qualified. This increases their educational and employment inequality. However, it is unclear whether this general finding also applies to participation in CVET when new technologies are introduced in companies. Companies could have an interest in the deployment of all their employees. The introduction of new technologies in a company context could lead to people with professional qualifications as well as those with higher qualifications taking part in CVET. Using the Linked Personnel Panel (LPP) and the IAB Establishment Panel, we investigate whether the participation of employees with university-level education and upper secondary vocational education differ if the participation in CVET is attributed directly to the introduction of technology in the workplace. The outcomes show that the more highly qualified use forms of self-study more frequently. However, there are only marginal differences between highly qualified and professionally qualified employees when it comes to the use of courses as part of in-house training.

**Keywords** Establishment panel, Continuing vocational education and training (CVET), In-company training, Digitalization, Labour market, Linked personnel panel, Qualification, Staff training, Technology, Workplace

**JEL Classification** J24, M53, O15, O33

## 1 Introduction

The use of new technologies is sometimes accompanied by fears of significant job losses (Arntz et al. 2016; Brynjolfsson and McAfee 2014; Frey and Osborne 2017; Josten and Lordan 2019; Nedelkoska and Quintini 2018). This holds true even if rehiring or creation of new jobs is taken into account (Acemoglu and Restrepo 2019; Autor 2019; Bessen et al. 2025). However, other authors consider such a scenario unlikely. Occupations and activities change successively and, in many cases, remain the same (Bonin et al. 2015; Dengler and Matthes 2018). In order to prepare employees for changes in activities, an intensification of company-based continuing vocational education and training (CVET) and in-company training is suggested (ibid.). Company-based CVET, which is the focus of this study, is generally understood to mean employee training activities that are intended to compensate for the changed skills requirements in the company (Sonntag and Schaper 2007: 573). However, CVET is characterized by selective access, as the highly qualified are comparatively more likely to participate in company-based CVET

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(Albert et al. 2010; Bellmann 2003; Campaner et al. 2022; Taylor and Urwin 2001). Emphasized is the so-called Matthew effect (Blossfeld et al. 2020; Boeren 2009; Lee and Desjardins 2019) or cumulative advantage/disadvantage effect (O'Rand and Henretta 1999). Accordingly, initial educational inequalities persist over the life course, as highly qualified workers continue to build up their comparative advantages in the labor market. At the same time, the less qualified workers find it harder to keep up with technological progress (Dauth 2020; Frey and Osborne 2017). In the following, the question will be examined as to whether vocationally qualified people, compared to those with university qualifications, participate to a lesser extent in company-based CVET when new (digital) technologies are introduced in the workplace or not.

Approximately two-thirds of each age cohort in Germany have gone through a vocational (dual) training (Michaelis et. al. 2022), in which they follow the general school education with a company-school vocational training of usually three years (Bosch and Charest 2008). Given their lower participation in CVET compared to graduates of graduates of universities of applied sciences and universities, the question arises as to whether people with vocational qualifications participate more in CVET when there is a specific reason for qualification at the workplace, namely the introduction of new technologies. Employees may wish to secure their position in the company by participating in training. Companies may have a vested interest in this, since a readily available workforce with appropriate vocational skills can be a promising basis for both investment decisions in technology and further training for this pre-qualified workforce (ibid.; Doeringer 1967; Lutz et al. 2007). Further training in new technologies could counteract a cumulative advantage/disadvantage effect for professionally qualified workers compared to graduates of universities of applied sciences or universities.

A major problem in research on digitalization in companies is the construction of a reliable and largely time-stable survey measure for technologies, hardware and software applications in order to accurately capture the state of digitalization in the respective companies at different points in time. The literature contains instruments such as the level of investment in modern information and communication technologies (Janssen et al. 2018; Lehmer and Matthes 2017) or information on types of digitally supported technologies in a company (Baethge-Kinsky 2020; Ohlert et al. 2022). This information is often collected in aggregated form at the company level. The effects of new technology are assumed to be the same for all employees. However, such effects do not necessarily apply to all employees or even to many employees (Baethge-Kinsky 2020; Dengler and Matthes 2018; Janssen et al. 2018). Furthermore, when comparing studies over time, capturing the current state of technology is often accompanied by a changing list of items, due to the very rapid change of technical devices or software programs. The lack of consistent panel elements on software or machines makes causal explanations of possible effects of digitalization difficult. In addition, heterogeneous use of different technologies, the frequency of which also varies between qualification groups, are inadequately represented in most studies. Furthermore, it should be noted that different forms of CVET, such as courses or self-learning at the workplace, can specifically characterize in-company training, and different qualification groups can use such different forms of training to varying degrees (Laible et al. 2020; Ehlert 2017).

Below we use the Linked Personnel Panel (LPP) and the IAB Establishment Panel. With this data, the problems can be at least partially addressed compared to other data sets. We take into account that effects of participation in CVET can differ according to the individual's level of education, as well as according to the technology used at the workplace or the form of CVET. We analyze whether employees with university level education and employees with upper secondary vocational education participate with the same or different probability in different forms of CVET and if they are equally or differently likely to take part in one of the various forms of CVET, when a technological change occurs in their workplace.

In the section on the state of research, the research question and theoretical assumptions, the relationship between certain technologies and CVET, as well as the relationship between formal education level and CVET, is examined in more detail. The methods used are explained and the data set and the composition of the sample are described in more detail. This is followed by results of the estimations and finally a discussion of the results.

## 2 State of research

### 2.1 Importance of in-company training

CVET can be divided into three forms (Callanan et al. 2011; European Commission 2000: 8; Lischewski et al. 2020). *Formal CVET* is associated with the goal of higher formal educational attainment. According to data from the Adult Education Survey 2018 (AES), which Kohl (2021) presents, formal education in adulthood accounts for an average of 11 percent of educational activities in Germany as a whole. Younger adults participate in these formal education activities, e.g. to obtain a higher educational qualification such as a (delayed) A-levels or bachelor's degree, considerably more often. For those over 35 years old, participation in these educational activities decreases to less than 1% after completing the vocational and university-level education phases (ibid: 215). Formal CVET is not considered in our study.

We focus on *non-formal CVET.* This refers to course-based CVET within or outside the company, which involves the development and acquisition of specific competencies or adaptations during the employment phase (Lischewski et al. 2020; von Rosenbladt et al. 2008). This form of CVET accounts for about 52% of all CVET (Kohl 2021: 223).

*Informal CVET* is also included in our study. It takes place outside of courses, for example directly at the workplace or privately (Lischewski et al. 2020). Examples include self-study through books, learning programs or instruction by other colleagues. In the context of this article, this also includes familiarizing yourself with new technologies and trying them out by themselves. 45% of respondents in the AES use this form of CVET (ibid.: 236).

There can be different outcomes that indicate the effects of CVET. First, there is unanimity that professional CVET has a positive impact on people's employability (Campaner et al. 2022; Dütsch and Struck 2014; Ramos and Harris 2012; Zeyer-Gliozzo 2020). In some cases, positive effects such as higher intra-firm mobility (Pfeifer et al. 2013; Dieckhoff 2007; Li et al. 2000), higher wages (Dauth 2020), or greater employment stability (Dütsch and Struck 2014) are reported. In the context of new technologies, this is ensured by updating or acquiring new skills through courses, targeted informal learning or instruction, as well as through machines and software that promote learning and the availability of time for learning (Ford et al. 2018). In companies, CVET and newly adapted skills are therefore often accompanied by a decrease in the share of easily automatable activities (Autor et al. 2003; Autor and Dorn 2013; Dauth 2020; Frey and Osborne 2017). It should be noted that all the positive effects of CVET listed above are dependent on the transfer and anchoring of the skills learned in daily work performance (Ford et al. 2018).

Many authors believe that new technologies as for example digitalization will lead to a new form of polarization of the labor market (Autor and Dorn 2013; Bonin et al. 2015; Frey and Osborne 2017; Goos et al. 2014; Goos and Manning 2007). They argue that in the current phase of digitalization, there is a higher automation risk for many employees in the middle of the professional skill range. The reason is that many of their occupational activities are characterized by high proportions of routine tasks (Autor and Dorn 2013). Here, successful participation in CVET could lay the foundation for new not (easily) standardizable job profiles, such as planning, control, consulting, development, quality assurance, and the like, among those with upper secondary vocational education. A change in activities supported by CVET can transform the relationship between technology and human labor from a substitutive to a complementary one. A wide variety of skill groups that exist in companies could be trained to meet changing job requirements that arise as new technologies are introduced. This transformation would promote an increase of skills, in productivity, and preserve employment (Genz et al. 2019; Konings and Vanormelingen 2015). This contrasts with the finding that employees with lower or medium vocational qualifications less often and employees with higher (academic) qualifications in particular participate disproportionately in general more often in CVET (Albert et al. 2010; Bellmann 2003; Campaner et al. 2022; Taylor and Urwin 2001).

Human capital theory cost–benefit calculations (Becker 1962), suggest that employees will invest more time and effort in CVET (e.g. in courses) or bear the costs if they expect returns on investment. These, in turn, are to be expected if there is a longer anticipated period of benefit from CVET (Taylor and Urwin 2001; Becker 1962). This goes hand in hand with the fact that older employees are less likely to participate in CVET or that CVET is more likely to take place if it has a direct and therefore promising connection to the activity carried out (Wenzelmann and Müller 2018). In addition, it is expected that more highly qualified education groups participate in CVET more often than, for example, graduates of dual training, because the duration and level of education are associated with successful and positive learning experiences that promote further learning (Slaten et al. 2019) or facilitate a decision for further training. Companies invest primarily in the CVETof people if it can be expected that the improved adaptation of their skills and abilities to the requirements of the job will be accompanied by increased productivity and that the costs of CVET will be amortized over time as a result. The latter implies that firms prefer to invest in the human capital of higher-skilled employees (Asplund 2005; Taylor and Urwin 2001; Arrow 1973). Thus, as new technologies are introduced, CVET could further enhance the cumulative advantage/disadvantage effect described in the introduction (Blossfeld et al. 2020; Lee and Desjardins 2019; Boeren 2009; O'Rand and Henretta 1999). However, it is unclear whether and to what extent such an effect actually affects employees with dual, upper secondary education and in-company vocational training in companies when new technologies are introduced. If they participate less in CVET than, for example, people with a university education, then there is a risk that this group will not acquire skills for new forms of production.

### 2.2 Company-based CVET offerings and employee demand

As we look at the job activities of different qualification groups in companies, differences appear in terms of the technology used (Brynjolfsson and McAfee 2014) and the forms of CVET. These are to be taken into account in analyses.

Highly qualified workers have very often perform many activities at their jobs that are difficult to automate (Bonin et al. 2015; Dengler and Matthes 2018; Frey and Osborne 2017). The use of new technologies is often accompanied by moderate changes to an e.g. new software application. CVET in this case often functions as a minor adjustment and is utilized to deepen the level of knowledge. In these cases, the thresholds for people, especially for informal learning alone or together with a colleague, are low and the costs of qualification are comparatively negligible.

Especially groups of people with medium qualifications are associated with higher risks of being affected by automation during their working lives. Consequently, they have to acquire comparatively extensive, in part fundamentally new qualifications in the course of CVET in order to be able to enter more protected fields of activity with newer requirement profiles. Such basic training is often organized in the form of courses. At the same time, though, the educational trajectories of precisely these groups of people show, on average, shorter periods of structured learning experiences than those of graduates of universities. The difference between comparatively low learning experiences and high learning requirements may be associated with an on average lower willingness to undergo CVET among groups with non-university qualifications (Nedelkoska and Quintini 2018). This is despite assuming that benefits for maintaining employability should, in principle, be high for skill groups with a higher risk of automation in the course of their careers and with fewer learning experiences.

We expect:

*H1* Employees who have a university of applied sciences or university degree participate in CVET proportionally more often than employees with a vocational qualification

### 2.3 Influence of technology and forms of CVET

When using technologies, a distinction can be made in particular between (application) *software* and *machines*.

In the course of the increased use of computers, *software* is now used in almost every area of business. Software primarily supports cognitive activities and therefore more likely occurs in professions with a corresponding focus. Routine activities, which are characterized by the sequence of fixed process steps, can be automated more easily by software (Autor et al. 2003). A large part of the automation potential of american occupations is therefore attributed to the use of software to substitute routine activities (Frey and Osborne 2017).

In particular, application software has a complementary effect on existing activities. It facilitates non-routine activities, which mostly includes creative activities (Autor et al. 2003; Frey and Osborne 2017). Social situations, such as those that can occur when working together are also supported by communication software or database systems. Such activities tend to emerge in professions for the more highly qualified or in leadership positions, such as management (Autor and Dorn 2013).

In this article, we distinguish between *simple software and mobile devices* and *complex software*. Simple software and mobile devices usually do not require a major learning effort, as similar software and mobile devices, such as cell phones, are already widely used. It can therefore be expected that their use is more intuitive to learn. Complex software, on the other hand, is more specific and less intuitive. Its use is therefore expected to require a more structured learning process. In contrast to application software, *machines, systems and robots* are mainly found in the manufacturing and processing sector and primarily support or replace manual activities (Bonin et al. 2015; Frey and Osborne 2017). In some cases, they are also used in research and development. However, considered particularly susceptible to automation are mainly manual routine activities (Autor et al. 2003) and job profiles changing in the direction of digital control, diagnosis, monitoring and technical troubleshooting, especially for those with vocational qualification. In addition to university graduates, it is primarily those with vocational qualifications who operate and maintain the new IT-controlled and networked machines, and they can be supported by more expert training.

We distinguish between classic production machines and modern production machines. While classic production machines, similar to simple software, are either easier to use or at least rudimentarily familiar from other contexts, making them easier to use, modern production machines can be significantly more complex to operate, which requires more extensive training.

When the various technologies are considered in relation to their complexity, the following hypothesis is put forward:

*H2* The use of complex software and modern, digitally controlled or networked production machines is more frequently associated with the attendance of non-formal course-based CVET by employees who hold a degree from a university of applied sciences or a university, in comparison to employees who hold a vocational qualification.

It is posited that the implementation of advanced and contemporary technologies may exert a deleterious effect on the career prospects of employees possessing vocational qualifications, through a selective negative participation in further vocational training.

In addition, courses must be distinguished from informal self-learning processes. Non-formal course-based CVET facilitate the initial learning of how to use a new application software or how to control, diagnose, maintain or service and troubleshoot machines. Here, trained specialists usually support active participation in the learning process. In our study, courses can be assumed to be fairly special training, since the courses are usually (co-)organized and (co-)financed by companies and are directly associated with the introduction of a previously introduced technology.

A distinction can be made between *internal* and *external* training courses (Dehnbostel 2010; Rausch 2012). Internal courses are offered by the company itself. The advantage here is comparatively low costs and flexibility in terms of time and content. This enables companies to offer customized courses, which facilitates the transfer of the skills learned. However, this type of course requires that the human capital to be taught is already available within the company, which is not always the case when implementing new technologies.

External courses, on the other hand, are run by third-party providers. This makes it easier to integrate new human capital from external experts into the company (Lischewski et al. 2020). The problem here can be whether the required courses are offered and whether their content can be transferred to the company's own work. However, it is often the case with new technologies that the manufacturers of these technologies themselves offer introductory courses for their own software or machines. However, due to the greater effort involved and the higher costs of participation, it can be assumed that primarily more highly qualified employees will receive external training.

We hypothesize:

*H3* Employees with a degree from a university of applied sciences or a university attend external training courses more often than employees with vocational qualification.

Small and medium-sized enterprises and companies that make comparatively extensive use of digital technologies, in addition to non-formal course-based CVET, also make use of informal digital learning programs or simulation programs to support autodidactic learning processes in order to increase the IT skills of their workforce (Seyda 2021). Some of the software used in companies is available on the market and is sold in large quantities (often also to private individuals). As a result, extensive self-study materials exist for many programs, such as manuals, video tutorials, digital assistants and learning programs.

While courses are characterized by formalized structures of the company or a provider, informal CVET takes place mostly on one's own initiative and requires autodidactic skills. Informal learning is more strongly linked to intrinsic motivations and personal learning characteristics than other forms of further CVET (Bereiter and Scardamalia 1989; Laible et al. 2020).

Employees with academic degrees have extensive experience with targeted autodidactic learning of skills compared to the less qualified. Sometimes, less qualified personnel has considerably fewer or no practice at all with this learning method and cannot fall back on positive experiences of targeted, independent learning (Candy 1991; Marsick and Watkins 2016). This increases the likelihood that the less qualified will refrain from expanding work content autodidactically (Illeris 2003; Rubenson and Desjardins 2009). Informal CVET is limited by the fact that self-study and trying out new technologies lacks coordinated exchange with colleagues and experts. Thus, this form of learning is more suitable for deepening and broadening existing skills and abilities. Courses with a guided practice phase or (informal) instruction by colleagues directly at the workplace, can offer detailed support for the acquisition and creation of new knowledge. Therefore, the acquisition and consolidation of new skills and abilities is easier in more direct and guided forms of learning.

We hypothesize the following:

*H4* Employees with a degree from a university or university of applied sciences are more likely to engage in self-study or to trying out new technologies in a targeted manner than employees with vocational training.

If people with upper secondary vocational education are less likely to pursue informal CVET on their own, then more compulsory non-formal course-based CVET would be particularly important for this employment group. Nevertheless, informal CVET can be complementary to non-formal course-based CVET and, because of its low-threshold access, can also be utilized. In particular, support from colleagues can be utilized or offered for the introduction of low-complex technologies across all qualification levels.

*H5* With regard to instruction by colleagues, which is sufficient when introducing low-complexity technology, we do not expect any differences between the observed qualification groups of graduates from universities of applied sciences, universities and with vocational qualifications

Specifically in regard to the use of software, machines, systems and robots, we expect companies to accompany the use of new machine technology with compulsory non-formal course-based CVET. Overall, it is still an open question whether a qualification gap between those with university-level education and those with school based vocational training will persist, be reduced or widened by in-company further vocational training.

## 3 Methods and descriptive

### 3.1 Methods and operationalizations

The IAB Establishment Panel and the fourth wave of the Linked Personnel Panel (LPP) from 2018 and 2019 are used to investigate the research questions. The IAB Establishment Panel is an annual survey of an average of 16,000 German companies and contains data on employment, company structure and other company characteristics (Bechmann et al. 2021). The LPP is a linked employer-employee dataset, which in wave 4 consists of 769 establishments and a sample of the employees working in them (N =6494) (Ruf et al. 2020). The LPP is a supplementary survey to the IAB Establishment Panel. Therefore, both data sets can be linked. The LPP survey is conducted every two years, with establishments and employees being surveyed alternately. The data are provided by the Research Data Center of the Institute for Employment Research (IAB). After excluding all incomplete data sets, 1957 employees from 363 companies whose workplaces have been equipped with new technologies in the last two years remain for the final working sample on which the regressions are based. At least one employee was surveyed in each of the 363 companies observed. 332 employees come from one company. This company forms the upper limit of the distribution of employees across the companies.[1] On average, 5.4 employees were surveyed per company.

The LPP is well suited for the purposes of this study, as not only extensive operational data, but also the characteristics of workplaces and individuals were collected. The fourth wave also includes, for the first time, extensive information on the use of new introduced technologies. Respondents were asked whether new technologies had been introduced in their personal work environment within the last two years, i.e., in the period since the last survey. If respondents answered this question in the affirmative, they were then asked more specifically, which of these technologies have had the greatest impact on their work. These open-ended individual responses were grouped into seven categories by the IAB. These were further condensed into the following four categories: 1. easy-to-use software and mobile devices, 2. computer-aided complex software that requires a IT-learning process, 3. classical production machines, including manufacturing equipment and tools and 4. modern (digital) production machines such as automated machines, robots or digital control systems which normally require an IT learning process (Ruf et al. 2020, cf. Appendix: Table 7). In addition, respondents were asked to indicate which non-formal course-based and informal CVET opportunities they used to acquire the necessary skills for this specific new technology in their workplace. Multiple responses were possible for this question. By connecting the training to the newly introduced technology, the purpose and content of this CVET are directly related to each other and thus allow us better to investigate a potentially causal linkage between both technology and the forms of CVET than was possible with previous data.[2]

There were employees who indicated that no new technology had been introduced within the last two years. Since it is not possible to decide whether the"non-users"have not actually used any of the specified technology for more than two years or have been using it for more than two years, this group was excluded from the analysis. Thus, our focus is on learning the necessary expertise via CVET for the use of newly introduced technology.

The employee qualifications were categorized according to the German Qualifications Framework (DQR). The DQR is an instrument that helps to map the equivalence of general, upper secondary vocational education and university-level education in eight levels (Federal Ministry of Education and Research, n. d.). The qualifications mapped in the LPP were categorized into three categories according to the DQR. Firstly, *upper secondary vocational education* corresponds to level four (DQR4) and five (DQR5) of the DQR. DQR4 requires the possession of at least three years of upper secondary vocational education. DQR5 includes vocationally learned occupations with shorter additional qualifications. Secondly, employees with a *bachelor´s degree from a university of applied sciences (UAS).* This corresponds to DQR6. And

[1] All regressions were also calculated without this company. No relevant changes in the results occur.

[2] Full questions are provided in Appendix Table 8

thirdly, persons who have earned a *master or a diploma degree from a university of applied sciences or a bachelor, master´s or diploma degree from a university,* according to DQR7 (see Appendix: Table 7).

In addition to the information from the LPP, data on whether the company covers the costs of CVET and whether employees were exempt from work for this purpose is provided. Furthermore, the existence of written plans for staff development and CVET from the 2018 and 2019 IAB company panel are taken into account. Information on plans was not collected in 2018 and was supplemented from the 2017 and 2019 waves.

First of all, logit regression analyses were used to determine whether the university graduates in our sample also participated above average in CVET, whether this related to the newly introduced technology or not (Table 4). This regression is carried out for our final working sample, on which all subsequent regressions are based (Working sample). In addition, the regression is also carried out for all available employees (Overall Sample), regardless of whether their workplaces have been equipped with new technologies in the last two years or not. This step ensures that our sample does not differ from the population in its probability of participating in CVET. This allows us to have more confidence when interpreting the meaning of our results. In a second step, logit regressions are calculated to map the participation in CVET as new technologies are introduced. In a first variation of the model, technology and qualification level are included without interactions to determine the effects separately. However, since the propensity to achieve higher levels of qualification and the need for CVET in different technologies can influence each other, we include interactions of the level of qualification and the technology in a second variation of the model.

Odds ratios are reported. They indicate the relative effect size in relation to the base category, whereby an effect size of 1 corresponds to the zero effect (No differences between the category under consideration and the baseline category). Lower impacts than in the base category are represented by values between 0 and 1, higher impacts by values greater than 1. The sole interaction effect shows the relative change in the relationship between an explanatory variable and the dependent variable depending on the value of another explanatory variable. When interpreting the strength of the interaction effects of odds ratios, the coefficients are multiplicative and not additive (Wooldridge 2012: 198ff, 792ff; Kohler and Kreuter 2017: 355ff). For all regressions, logit estimators were used (Aldrich 1984; Wooldridge 2013: 584ff). The required linearity when using logits for continuous variables is ascertained by including all variables as dummies. Furthermore, we ensured that there was no strong multicollinearity in the models and calculated the variance inflation factor (VIF) for all incorporated variables in all models (Wooldridge 2013: 94ff). This is particularly crucial when differentiating the effects of the technology in use and the qualifications of the user. To account for the interaction of establishment and employee levels and for the condition of the logit estimator for independence of residuals, all regressions incorporate clustered standard errors at the company level (Wooldridge 2013: 499ff). To ensure comparability of the outcomes, the sample was kept constant across all evaluations.

### 3.2 Description

The sample is presented in Table 1. Overall, there is sufficient heterogeneity in the data and our overall sample. It includes a majority of men (73%). The selection criterion that the workplace is characterized by the introduction of new technology within the last two years is accompanied with considerably higher proportions of graduates with a bachelor´s degree from a university of applied sciences (24%) and master´s degree from a university of applied science and university degrees (31%) than in the general working population, but persons with upper secondary vocational education still make up close to half of the sample (45%). Unqualified persons had to be excluded, as this group is not well represented in the data set and no reliable statements could have been inferred.

In the overall sample, the majority of employees work full-time (87%). The share of those employed in production is 38%, as the majority is employed in various service sectors making up 62%. The share of employees working in larger companies with more than 500 employees is 57%. In the last two years, mostly complex software was newly introduced to the work area of the respondents (52%). Easy-to-use software has presumably already been part of everyday work for a longer period of time and is mentioned somewhat less frequently as being recently introduced (27%). Classical and modern production machines were also mentioned less (21%). This is no surprise, as investment costs of machines are disproportionately higher than for the introduction of new software, and they are only used in special operating areas. We observe only small differences between our working sample and the overall sample data. Companies with over 500 employees have introduced new technologies somewhat more frequently in the last 2 years. At the same time, the proportion of university graduates in these companies is somewhat higher than in smaller companies. Such differences are controlled for in the following calculations by including these variables.

If we look at participation in CVET overall, the picture is clear: Around half of the respondents in the sample took part in CVET within the last two years (Table 1). Of

**Table 1** Description of the variables

| Variable | N (%) working sample | N (%) overall sample |
|---|---|---|
| Individual-level Variables | | |
| Professional qualification degree | | |
| - Upper secondary vocational education | 709 (36.23%) | 2740 (45.04%) |
| - UAS bachelor | 512 (26.16%) | 1448 (23.80%) |
| - UAS degree/university degree | 736 (37.61%) | 1896 (31.16%) |
| Used technology | | |
| - Easy-to-use software/mobile devices | 575 (29.38%) | 903 (26.88%) |
| - Complex software | 1002 (51.20%) | 1761 (52.43%) |
| - Classical production machines | 198 (10.12%) | 364 (10.84%) |
| - Modern (digital) production machines | 182 (9.30%) | 331 (9.85%) |
| CVET in general (Ref. No CVET) | 1085 (55.44%) | 2864 (46.07%) |
| Digital technology introduced in the last 2 years (Ref. No technology introduced) | 1957 (100%) | 4183 (69.86%) |
| CVET in new technology (multiple responses possible) | | |
| - No CVET in new technology | < 20 (< 1.02%) | 1135 (18.20%) |
| - Internal courses | 1177 (60.14%) | 2542 (60.87%) |
| - External courses | 386 (19.72%) | 832 (19.93%) |
| - Self-study | 1759 (89.88%) | 3697 (88.49%) |
| - Instruction by colleagues | 1735 (88.66%) | 3701 (88.60%) |
| Female | 435 (22.23%) | 1661 (26.64%) |
| Age | | |
| - < 36 years | 308 (15.74%) | 873 (14.00%) |
| - 36 to 50 years | 669 (34.18%) | 2016 (32.33%) |
| - > 50 years | 980 (50.05%) | 3346 (53.66%) |
| Inquisitive (Ref. Not inquisitive) | 710 (36.28%) | 2083 (33.47%) |
| New competencies needed for technology (Ref. No new competencies needed) | 908 (46.40%) | 1980 (47.41%) |
| Business unit | | |
| - Production | 694 (35.46%) | 2380 (38.31%) |
| - Sales/Marketing | 246 (12.57%) | 709 (11.41%) |
| - Cross-sectional functions/administration | 504 (25.75%) | 1331 (21.42%) |
| - Service | 513 (26.21%) | 1793 (28.86%) |
| Working in a team (Ref. not working in a team) | 1694 (86.56%) | 5124 (82.47%) |
| Part-time (Ref. Full-time) | 207 (10.58%) | 838 (13.48%) |
| Company level variables | | |
| Fixed plans for staff development in own company (Ref. No plans) | 1655 (84.57%) | 3052 (79.71%) |
| CVET in own company promoted in first half of the year (Ref. Not training promoted) | 1920 (98.11%) | 3749 (96.70%) |
| Works in company with … subject to social security contributions | | |
| - 50–99 employees | 113 (5.77%) | 441 (10.60%) |
| - 100–249 employees | 207 (10.58%) | 583 (15.04%) |
| - 250–499 employees | 318 (16.25%) | 667 (17.20%) |
| - 500 + employees | 1319 (67.40%) | 2216 (57.16%) |
| N | 1957 (100%) | 6235 (100%) |

these, the majority had a university degree (Table 2). This selectivity in favor of higher educational qualifications is in line with previous research findings on general participation in CVET in companies (Albert et al. 2010; Bellmann 2003; Campaner, 2022; Taylor and Urwin 2001).

But what happens if we do not consider CVET in general, but rather CVET due to the introduction of new technologies directly at the workplace of the respondents? Both non-formal courses and informal forms of CVET are used intensively in companies to acquire competences for newly introduced technology (Table 2).

**Table 2** Description of further vocational training, qualification and technology (overall sample)

| | CVET in general | CVET in context of the introduction of new technology | | | | |
|---|---|---|---|---|---|---|
| | | Non-formal CVET Informal CVET | | | | |
| | | Internal courses % | External courses % | Self-study/trying out new technologies % | Instruction by colleagues | Number of forms of CVET used |
| Upper secondary vocational education | 33.52% | 60.14 | 16.41 | 82.07 | 90.29 | 2.49 |
| UAS bachelor | 52.32% | 67.25 | 25.58 | 90.96 | 89.31 | 2.73 |
| UAS master degree/university degree | 61.03% | 57.88 | 20.14 | 94.91 | 86.34 | 2.59 |
| Easy-to-use software/mobile devices | – | 49.17 | 10.75 | 93.36 | 87.49 | 2.40 |
| Complex software | – | 67.42 | 22.95 | 92.05 | 88.52 | 2.71 |
| Classical production machines | – | 53.57 | 20.05 | 79.12 | 92.03 | 2.45 |
| Modern (digital) production machines | – | 64.35 | 31.82 | 81.27 | 93.35 | 2.71 |

Multiple responses were possible for type of CVET

**Table 3** Description of the relationship between qualification and technology use (Overall Sample)

| | Upper secondary vocational education % | UAS Bachelor % | UAS master degree/ university degree % |
|---|---|---|---|
| Easy-to-use software/mobile devices | 22.78 | 21.56 | 55.67 |
| Complex software | 33.49 | 28.63 | 37.88 |
| Classical production machines | 73.12 | 19.08 | 7.80 |
| Modern (digital) production machines | 67.50 | 24.06 | 8.44 |

Within non-formal course-based CVET, internal courses are most prevalent (ibid.). Informal CVET tends to have low barriers to entry and is the most widespread, as expected. It is notable that employees of different skill levels tend to participate in CVET in connection with the introduction of new technology (and in contrast to CVET in general) to a comparable extent (ibid.). On average, each qualification group used between 2.49 and 2.73 different types of CVET to learn how to use new technologies. The use of more complex technologies also contributes to participation in several forms of CVET. While an average of 2.4 forms of CVET are used to learn simple software, 2.71 forms of CVET are used for complex software and modern production machines (ibid.). The need to acquire skills when new technology is introduced seems to compensate for an otherwise different participation of employees with different levels of education.

As expected, the use of technology varies with the qualifications of the respondents. Workplaces of employees with professional qualifications are proportionately more often characterized by newer technology in production machines, and those of employees with higher academic degrees are more often characterized by new software (Table 3). The relationship between qualification and technology used is confirmed. It is clear that new software has primarily been introduced in workplaces for employees with a UAS master´s or university degree in the last two years. Interpretations that concern connections between university qualifications and production machines should be done with more caution.

## 4 Regression outcomes

### 4.1 General CVET

Now we turn our attention to the results of the regressions. First, we will have a look at CVET in general. UAS bachelor graduates are about two times more likely to participate in CVET, and university graduates two and a half times more likely to do so than those with upper secondary vocational education (Table 4). This outcome supports, once again, the estimate of earlier research findings (Albert et al. 2010; Bellmann 2003; Campaner et al. 2022; Taylor and Urwin 2001) and can serve as a benchmark for the analysis of CVET in connection with the introduction of new technology.

At this point, we can support H1. We can also detect a Matthew effect in our data with regard to CVET in general. This means that our sample behaves similarly to the population observed in other studies. However, we cannot yet make a statement about the influence of technology on this behavior, which is the actual core question of this study. In addition, familiar trends can also be observed with regard to age. Employees over the

**Table 4** Regression outcomes: general CVET (logit regression)

| Variable | Working sample odds ratio (standard error) | Overall sample odds ratio (standard error) |
|---|---|---|
| Professional qualification degree (Ref. upper secondary vocational education) | | |
| - UAS bachelor | 2.045*** (0.234) | 2.221*** (0.187) |
| - Master degree/University degree | 2.486*** (0.284) | 2.757*** (0.260) |
| Female (Ref. Male) | 0.958 (0.129) | 0.977 (0.098) |
| Age (Ref. Adult of 35 years or younger) | | |
| - 36—50 years | 0.808 (0.117) | 0.799** (0.082) |
| - Older than 50 years | 0.539*** (0.074) | 0.581*** (0.061) |
| Business Unit (Ref. Production): | | |
| - Sales/Marketing | 1.385* (0.231) | 1.505** (0.253) |
| - Cross-sectional functions/administration | 1.620*** (0.183) | 1.716*** (0.193) |
| - Services | 1.414*** (0.169) | 1.739*** (0.163) |
| Part time (Ref. Full time) | 0.750* (0.123) | 0.703*** (0.091) |
| Inquisitive (Ref. Not inquisitive) | 1.130 (0.090) | 1.134* (0.076) |
| Company size in social security (Ref. 50–99 employees): | | |
| - 100–249 employees | 0.812 (0.209) | 0.802 (0.150) |
| - 250–499 employees | 0.665* (0.163) | 0.759 (0.138) |
| - 500 + employees | 0.865 (0.195) | 1.000 (0.175) |
| Working in a team (Ref. No) | 1.707*** (0.230) | 1.515*** (0.139) |
| One-the-job training promoted by the company (Ref. not promoted) | 2.203*** (0.521) | 2.816*** (0.561) |
| Fixed staff development plans in company (Ref. no plan) | 1.316* (0.197) | 1.479*** (0.181) |
| Constant | 0.232*** (0.081) | 0.110*** (0.030) |
| McFadden $R^2$ | 0.072 | 0.090 |
| N (employees) | 1957 | 3506 |
| N (companies) | 363 | 526 |

*Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Cluster robust standard errors in parentheses

age of 50 participate in CVET only about half as often as employees up to the age of 35. There is no difference with regard to gender. The promotion of CVET in the company and the existence of fixed plans for staff development both have a significantly positive effect on participation in CVET. We observe no significant differences between our working sample and the overall sample data. This supports our assumption that our work sample does not differ significantly from the overall sample Therefore, we can assume that there is no selection bias for access to new technologies within the observed qualification levels.

### 4.2 CVET in the form of courses

For non-formal course-based CVET, students with a bachelor´s degree from a university of applied sciences are 26% more likely to participate in internal courses (Table 5, Model 1a) and 82% more likely to participate in external courses (Table 5, Model 2a) than those with upper secondary vocational education. Graduates with a master's degree and university graduates are 30% more likely to take part in external courses.

However, these effect sizes are considerably smaller than those that distinguish the introduced technology. After the introduction of complex software, the probability of participation in internal and external courses doubles compared to the introduction of simple software or mobile devices (Table 5, Models 1a and 2a). Modern (digital) production machines increase the propability of participation in internal courses by 42% (Table 5, Model 1a) and by 110% in external courses (Table 5, Model 2a) compared to those with upper secondary vocational education. So far, our results support the preliminary considerations to complex and modern technologies in context of H2: More complex technologies appear to increase the participation of employees in CVET more than simple technologies, regardless of the formal education of the employees.

When the relationship between respondents' educational attainment and the technology they use at work is taken into account in the form of interaction effects, the base effects of technology and educational attainment are substantially reduced (Table 5, Models 1a and 2a compared to Models 1b and 2b). The base effect for the use

**Table 5** Regression results: non-formal course-based CVET (logit regressions)[1]

| Variable | Internal courses | | External courses | |
|---|---|---|---|---|
| | Model 1a | Model 1b | Model 2a | Model 2b |
| Professional qualification degree (Ref. upper secondary vocational education) | | | | |
| - UAS bachelor | 1.260* (*0.153*) | 1.179 (*0.284*) | 1.821*** (*0.249*) | 2.327** (*0.838*) |
| - UAS master/university degree | 0.955 (*0.120*) | 0.690 (*0.198*) | 1.301* (*0.200*) | 1.098 (*0.345*) |
| Technology (Ref. easy-to-use software/mobile devices) | | | | |
| - Complex software | 2.059*** (*0.264*) | 1.478* (*0.337*) | 2.123*** (*0.303*) | 2.336** (*0.816*) |
| - Classical production machines | 1.059 (*0.209*) | 0.867 (*0.292*) | 1.803*** (*0.354*) | 1.367 (*0.503*) |
| - Modern (digital) production machines | 1.418** (*0.239*) | 1.340 (*0.302*) | 2.107*** (*0.438*) | 1.962* (*0.721*) |
| Interactions | | | | |
| Complex software | | | | |
| - UAS bachelor | | 1.139 (*0.324*) | | 0.612 (*0.258*) |
| - UAS master/university degree | | 1.873* (*0.678*) | | 1.104 (*0.410*) |
| Classical production machines | | | | |
| - UAS bachelor | | 1.307 (*0.593*) | | 1.322 (*0.689*) |
| - UAS master/university degree | | 0.850 (*0.569*) | | 2.825* (*1.724*) |
| Modern (digital) production machines | | | | |
| - UAS bachelor | | 0.762 (*0.281*) | | 0.911 (*0.606*) |
| - UAS master/university degree | | 0.661 (*0.313*) | | 1.249 (*0.779*) |
| Female (Ref. Male) | 0.873 (*0.115*) | 0.872 (*0.114*) | 0.552** (*0.162*) | 0.539** (*0.162*) |
| Age (Ref: Adult of 35 years or younger) | | | | |
| - 36—50 years | 1.413* (*0.254*) | 1.425* (*0.257*) | 1.035 (*0.257*) | 1.033 (*0.257*) |
| - Older than 50 years | 1.665** (*0.337*) | 1.678** (*0.340*) | 1.024 (*0.176*) | 1.010 (*0.176*) |
| Business Unit (Ref. Production): | | | | |
| - Sales/Marketing | 1.410 (*0.329*) | 1.403 (*0.333*) | 1.087 (*0.209*) | 1.071 (*0.205*) |
| - Cross-sectional functions/administration | 1.162 (*0.188*) | 1.179 (*0.189*) | 1.003 (*0.179*) | 1.001 (*0.177*) |
| - Services | 1.305** (*0.176*) | 1.305* (*0.177*) | 1.123 (*0.166*) | 1.130 (*0.169*) |
| Part time (Ref. Full time) | 0.852 (*0.165*) | 0.862 (*0.171*) | 1.147 (*0.355*) | 1.144 (*0.367*) |
| Inquisitive (Ref. Not inquisitive) | 0.935 (*0.106*) | 0.939 (*0.106*) | 1.145 (*0.115*) | 1.132 (*0.113*) |
| New competencies needed for technology (Ref. No competencies required) | 2.560*** (*0.234*) | 2.587*** (*0.237*) | 2.618*** (*0.328*) | 2.618*** (*0.325*) |
| Company size in social security (Ref. 50–99 employees): | | | | |
| - 100—249 employees | 1.053 (*0.263*) | 1.087 (*0.271*) | 1.364 (*0.406*) | 1.348 (*0.404*) |
| - 250—499 employees | 1.180 (*0.292*) | 1.208 (*0.298*) | 0.863 (*0.253*) | 0.862 (*0.256*) |
| - 500 + employees | 1.010 (*0.224*) | 1.031 (*0.225*) | 0.952 (*0.263*) | 0.954 (*0.266*) |
| Working in a team (Ref. No) | 1.322** (*0.168*) | 1.325** (*0.165*) | 1.203 (*0.247*) | 1.192 (*0.242*) |
| Further vocational training promoted by company (Ref. not promoted) | 3.534*** (*0.738*) | 3.608*** (*0.777*) | 1.676 (*0.612*) | 1.702 (*0.605*) |
| Fixed staff development plans in company (Ref. No plan) | 1.091 (*0.191*) | 1.101 (*0.194*) | 1.167 (*0.240*) | 1.156 (*0.235*) |
| Constant | 0.084*** (*0.031*) | 0.095*** (*0.040*) | 0.028*** (*0.014*) | 0.029*** (*0.016*) |
| McFadden $R^2$ | 0.082 | 0.0867 | 0.0763 | 0.0797 |
| N (employees) | 1957 | 1957 | 1957 | 1957 |
| N (companies) | 363 | 363 | 363 | 363 |

*Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. Cluster robust standard errors in parentheses

[1] To facilitate interpretation and comparison, models 1b and 2b are presented graphically also in the Appendix

of complex software is reduced from 105% to merely 47% higher odds of participation in internal courses than for the use of simple software (Table 5, Models 1a and 1b). Especially for graduates of a university, the interaction effect with complex software is comparatively strong, indicated by 87% higher odds of participation in comparison to those with upper secondary vocational education. However, both of these effects are only significant at the

10% level. For external courses, positive effects remain for more digital production machines. They show similar effect sizes compared to the model without interactions (Table 5, Models 2a and 2b).

If the use of technology by employees with different educational qualifications is taken into account (Table 5, Model 1b), it becomes clear that university graduates participate in internal courses somewhat more frequently when complex software is introduced. Apart from this, our results largely refute H2. Complex software and modern production machines increase the likelihood of participation in non-formal training courses, largely irrespective of the level of formal education. Furthermore, there is no evidence in the interacting models that the use of complex software and modern production machinery has a different effect on certain skill levels than on others, apart from a slightly stronger effect of complex software on university graduates. We refrain from interpreting the weakly significant effect of more frequent participation in external courses after the introduction of classical production due to a very small sample size of university graduates with jobs using classical production machines. It is possible that these are external instructions or courses in the context of purchasing decisions of machines and equipment technology.

As we recapitulate in our hypothesis, it is evident that a Matthew effect on participation in CVET cannot be observed when new technologies are installed at workplaces. On the one hand, graduates from universities of applied sciences and bachelor's graduates appear to be more likely to participate in CVET measures (Table 4).

On the other hand, this finding must be contextualized by the effects of using new technology, which is accompanied by a largely non-selective participation in non-formal CVET of all qualification groups (Table 5). Non-formal course-based CVET in the context of an in-company introduction of new technology thus shows a different pattern than education-selective participation in general CVET. For non-formal course-based CVET, the effects of selection to the disadvantage of upper secondary vocational education individuals (compared to university graduates) are greatly reduced when new technologies are used. We can therefore carefully reject H3. We find no clear evidence that employees with a university of applied sciences or university degree participate more frequently in internal courses and only partial evidence of higher participation in external courses than employees with vocational qualifications. The significant effects in Model 2a for the higher qualification levels are stratified in Model 2b. Here, there are only significant effects in the base effect of employees with a UAS bachelor's certificate who work with simple software and an effect of university graduates who work with traditional production equipment, which is difficult to interpret due to the low number of cases. However, the baseline effect for participation in external training for employees with a UAS bachelor's certificate was high and significant in the interacted model (Model 2b). However, it is difficult to draw clear conclusions from the results of this intermediate group. We are unable to identify a uniform picture of technology-independent higher participation in CVET by higher qualified employees. Therefore, we carefully reject H3. The introduction of technology is a much stronger driver for participation in non-formal CVET than in formal education. This applies to all models.

### 4.3 Informal CVET

While non-formal course-based CVET must be planned in advance in terms of timing and content and is sometimes mandated by the company, informal CVET is generally easier to implement. Time windows are required in the course of work as well as an inclination or self-motivation for self-study or trying out the new technology in the workplace. In line with expectations, employees with higher qualifications, and thus generally longer learning experiences and comparatively more autonomous scope of action at the workplace, are more likely to educate themselves through self-study and trying out new technology than employees with upper secondary vocational education (Table 6, Model 3a). In the interaction model, an insightful picture emerges. While employees with a UAS bachelor's degree do not differ from employees with a vocational degree, the base effect for university graduates shows a fourfold increase in the prevalence of self-study (Table 6, Model 3b).

In the interaction model of technology introduction and qualification level (Table 6, Model 3b), none of the effects of technology on participation in informal CVET can be significantly distinguished from one another. However, significant and negative interaction effects (smaller than 1) are unveiled for UAS master and university graduates with the production machines (approximately a mere 1/4 for classical and approximately just 1/8 for digital production machines). A possible explanation is that the coefficient of university graduates in Model 3a is biased downward by their lower self-study in the use of production machines. In the interaction Model 3b, the effects are differentiated for the various production machines. Most notably, the previous and already high odds ratio of 130% for UAS master and university graduates using self-study was increased even further to 295% in the interaction model, especially for easy-to-use software (effect of the reference category remaining in the education variable in the interaction). These results are consistent with H4. There are very few obstacles to participating in CVET via instruction by colleagues.

**Table 6** Regression results—Informal CVET (logit regressions)[1]

| Variable | Self-study/Trying out | | Instruction by colleagues | |
|---|---|---|---|---|
| | **Model 3a** | **Model 3b** | **Model 4a** | **Model 4b** |
| Professional qualification degree (Ref. upper secondary vocational education) | | | | |
| - UAS bachelor | 1.755*** (0.333) | 1.433 (0.548) | 1.124 (0.239) | 0.803 (0.291) |
| - UAS master/university degree | 2.304*** (0.514) | 3.975*** (1.430) | 0.752 (0.147) | 0.869 (0.262) |
| Technology (Ref. easy-to-use software/mobile devices) | | | | |
| - Complex software | 1.069 (0.233) | 1.158 (0.380) | 0.863 (0.167) | 0.808 (0.270) |
| - Classical production machines | 0.529** (0.146) | 0.666 (0.240) | 1.055 (0.298) | 1.276 (0.567) |
| - Modern (digital) production machines | 0.610* (0.166) | 0.803 (0.271) | 1.254 (0.467) | 1.560 (0.774) |
| Interactions | | | | |
| Complex software | | | | |
| - UAS bachelor | | 1.606 (0.759) | | 1.793 (0.803) |
| - UAS master/university degree | | 0.580 (0.290) | | 0.912 (0.343) |
| Classical production machines | | | | |
| - UAS bachelor | | 1.024 (0.640) | | 1.098 (0.831) |
| - UAS master/university degree | | 0.292* (0.199) | | 0.382 (0.353) |
| Modern (digital) production machines | | | | |
| - UAS bachelor | | 1.225 (0.819) | | 1.408 (1.314) |
| - UAS master/university degree | | 0.120*** (0.084) | | 0.253 (0.242) |
| Female (Ref. Male) | 1.154 (0.325) | 1.179 (0.333) | 1.405 (0.405) | 1.445 (0.420) |
| Age (Ref. Adult of 35 years or younger) | | | | |
| - 36—50 years | 0.692 (0.272) | 0.675 (0.265) | 1.325 (0.261) | 1.311 (0.267) |
| - Older than 50 years | 0.703 (0.256) | 0.686 (0.251) | 1.529** (0.299) | 1.518** (0.306) |
| Business Unit (Ref. Production): | | | | |
| - Sales/Marketing | 1.551 (0.433) | 1.610* (0.429) | 0.593* (0.160) | 0.602* (0.160) |
| - Cross-sectional functions/administration | 2.359*** (0.505) | 2.423*** (0.529) | 0.605* (0.159) | 0.617* (0.161) |
| - Services | 1.324 (0.233) | 1.329 (0.237) | 0.677* (0.155) | 0.678* (0.152) |
| Part time (Ref. Full time) | 0.900 (0.283) | 0.920 (0.289) | 0.966 (0.264) | 0.967 (0.267) |
| Inquisitive (Ref. Not inquisitive) | 1.227 (0.236) | 1.219 (0.230) | 0.815 (0.128) | 0.814 (0.126) |
| New competencies needed for technology (Ref: No competencies required) | 1.530*** (0.224) | 1.559*** (0.233) | 1.667** (0.355) | 1.681** (0.356) |
| Company size in social security (Ref. 50–99 employees): | | | | |
| - 100—249 employees | 0.738 (0.262) | 0.784 (0.279) | 1.023 (0.369) | 1.067 (0.386) |
| - 250—499 employees | 0.871 (0.311) | 0.897 (0.320) | 1.214 (0.405) | 1.247 (0.416) |
| - 500 + employees | 1.033 (0.332) | 1.034 (0.331) | 1.079 (0.339) | 1.092 (0.344) |
| Working in a team (Ref. No) | 1.239 (0.280) | 1.245 (0.280) | 1.615*** (0.296) | 1.634 (0.298) |
| Further vocational training promoted by company (Ref. not promoted) | 1.292 (0.681) | 1.245 (0.662) | 1.131 (0.595) | 1.104 (0.590) |
| Fixed staff development plans in company (Ref. No plan) | 0.772 (0.193) | 0.787 (0.197) | 1.671*** (0.283) | 1.695*** (0.288) |
| Constant | 4.467** (3.303) | 3.846* (2.914) | 2.686 (1.664) | 2.569 (1.674) |
| McFadden $R^2$ | 0.0778 | 0.0858 | 0.0396 | 0.0401 |
| N (employees) | 1957 | 1957 | 1957 | 1957 |
| N (companies) | 363 | 363 | 363 | 363 |

[1] To facilitate interpretation and comparison, models 3b and 4b are presented graphically also in the Appendix

*Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. Cluster robust standard errors in parentheses

Here, no significant differences can be found between the training qualifications, the technologies used both in the models with and without interactions (Table 6, Models 4a and 4b). H5 can therefore also be supported.

In contrast to non-formal course-based CVET, we see a Matthew effect for university graduates, UAS bachelor, in informal, especially self-employed, CVET, which corresponds to H4. Highly qualified individuals are active on their own and demonstrate autodidactic skills.

Employees with an intermediate level of education are less likely to make use of these forms of CVET. However, they take part in further training in the form of courses just as often as university graduates.

### 4.4 General trends and control variables

The size of the company is insignificant in each regression. Covering the costs of CVET, on the other hand, leads to greater use of in-house courses by companies and to more frequent participation by employees, than if employees have to pay for the training themselves. (Table 5, Models 1a and 1b). Another interesting result is that older people in particular are increasingly taking part in internal training courses (Table 5, Model 1a). These results correspond with the findings of Gegenfurtner and Vauras (2012), who found no correlation between age and motivation to learn. Apart from external courses, in which women participate less frequently (Table 5, Models 2a and 2b), no differences with regard to gender were found. There are only isolated differences in the business units. However, production clearly stands out here, where instruction by colleagues is found more frequently compared to other business units (Table 6, Models 3a and 3b). Working in teams is, unsurprisingly, positively related to the acquisition of new competencies through explanation by others (Table 6, Models 4a and 4b). Interestingly, we find almost no differences between age groups in the likelihood of participating in external courses or self-study (Table 5, Model 2a and 2b; Table 6, Model 3a and 3b). However, we can observe that older employees are more likely to take part in internal courses or receive further training from colleagues. (Table 5, Model 1a and 1b; Table 6, Model 4a and 4b). In all the results we see the trend that both sides, companies, and employees, carry out further training when new technologies are introduced into the workplace. We do not see a partial setback of those with professional qualifications or even older people, at least when it comes to taking part in non-formal course-based CVET.

## 5 Discussion

With regard to general participation in CVET, our study initially supports the existence of a Matthew effect. Highly qualified employees participate in CVET significantly more often than employees with upper secondary vocational education (Table 4), which is in line with H1.

However, this general finding of a Matthew effect of origin- and experience-dependent education and training (Blossfeld et al. 2020; Boeren 2009; Lee and Desjardins 2019; O'Rand and Henretta 1999) is only validated to a limited extent when focusing on CVET for the introduction of new (digital) technologies. While university graduates participate more frequently in independent informal CVET (Table 6), which supports H4, this pattern is largely unrecognizable in non-formal course-based CVET (Table 5). We find only a slight tendency for higher participation in external training for employees with a UAS bachelor's certificate, which is why we cautiously reject H3 (Table 5, Mod 2a and 2b). We have shown that complex software and digital production machines in particular are associated with a significant increase in participation of non-formal course-based CVET (Table 5). H2 can therefore be fully supported. We thereby unveiled that the respective technologies at the workplace vary with the different qualification levels.

Both university graduates and those with upper secondary vocational education receive and make use of the opportunity for CVET in companies when they are confronted with new technologies. While there are clear differences in the initiative in self-study in favor of university graduates, non-formal course-based CVET is well accepted by all employees. This means that companies, which in Germany can be regarded as the main vocational training organizations, play an important role for those employees who have been exposed to new technologies at work in the last two years. Regardless of their qualifications, specialists and university graduates who apply technologies are supported. Unfortunately, we cannot determine what happened to the workers who did not get to these workplaces.

CVET in the use of new technologies promotes the productivity of employees. At the same time, it promotes, at least for this group, individual employability and thus contributes to coping with structural adjustment processes in general (Mayer and Solga 2008; van Laar et al. 2017).

Inequalities exist in informal CVET. These are not only explained by the technology used in the workplace. University graduates make disproportionately large use of self-study and trying out new technologies with less complex software. However, such software is used at almost all workplaces. The causes for the selective use of self-study and trying out new technologies could therefore lie not only in the reinforcement of individual learning or in uncertain experiences in self-learning, but also in the design of workplaces and learning environments that offer little in the way of incentives, structures, support and orientation for learning through trial and error (Bäumer et al. 2019; Decius et al. 2021; Wang et al. 2021). Motivating and supportive learning environments also for informal self-learning at workplaces of mostly upper secondary vocational education employees could prove suitable for reducing the inequalities that still exist in this form of CVET. Although self-study is more difficult with machines, there are still possibilities for this. Time periods could be given to handle new machinery independently of common work processes to facilitate further learning, e.g. 3D-printing and additive manufacturing. Supporting material for self-study, such as manuals, written instructional content or learning videos or simulation software can be made available.

## 6 Limitations

This study has several limitations. No robust evaluations could be conducted for employees without a professional qualification degree. In the LPP, and therefore in our sample, employees without a professional qualification degree are only represented in very small numbers. This group is strongly threatened by automation through new technologies. Unfortunately, due to the small number of cases in the LPP data, it is not possible to investigate their participation in CVET. This is unfortunate, given the social significance of this group.

The fact that the sample only includes employees who actively work with new technologies is associated with a second limitation. The model uses data on CVET that are directly related to the use of new technology at the employee level. This is only possible in the fourth wave of the LPP. It is therefore not possible to make statements about people who use newer (digital) technologies that were introduced more than two years ago and have not been updated recently. Moreover, we cannot make any statement about the anchoring and transfer of the skills learned in the non-formal course-based CVET. We can only observe participation in various forms of CVET as a primary condition for subsequent knowledge acquisition and transfer. However, the interviewees were specifically asked through which forms of CVET they had acquired the necessary skills to use the newly introduced technology. This means that we can at least assume a subjective learning success. Furthermore, we cannot take a position on the question of which circumstances based on individual or company lead to the introduction of new technologies at the workplaces of employees with certain qualifications. The focus of this study is therefore on participation in CVET in connection with the introduction of new technologies at the workplace of the employee surveyed in the study. This is precisely why the calculated models, and the validity of its results are not reduced by the underlying data and research design. In addition, we cannot make any statements about the effects of AI and large language models and the effect of their use on participation in CVET. Such technologies were not yet very widespread in the 2018 and 2019 survey period and were therefore not depicted in the data.

In this study we could also not observe whether, to what extent and especially under which conditions, including the qualification level of employees or in-company training activities, new technologies lead to a reduction or increase of employment or whether unemployment is increased or decreased. Further research is needed in this area.

## 7 Conclusion

The initial question of this study was whether a positive selectivity in access to (further) education and CVET for the highly qualified continues in the use of new (digital) technologies in companies, as described in many studies. Previous data sets and studies have not been able to provide sufficient data on this, as they have not taken into account the individual use of technology. In addition, forms of CVET are often insufficiently differentiated. This study attempts to compensate for this deficiency by evaluating the fourth wave of the LPP's company-employee survey. In this wave, for the first time, an in-depth relationship between technology and CVET was recorded.

We showcased, on the one hand, that with regard to general CVET, a Matthew effect can also be detected in the LPP data. On the other hand, when CVET is paired with the increased usage of technical and digital tools, a very different picture is portrayed. The Matthew effect was located in self-study and trying out new technologies among UAS master and university graduates. However, for non-formal course-based CVET, both internal and external, or instruction by colleagues, largely no differences were observed between employees of different qualification levels. The use of digital and complex technology in the workplace leads to a higher level of participation of non-formal course-based CVET for all qualification groups included in this study compared to participation in general CVET in the company.

We consider vocational and university graduates under the condition that new technologies have been introduced at their workplace. We find that there is no difference in the probability of participation in CVET, at least with respect to non-formal course-based CVET. Whether and to what extent companies that introduce new technologies may want to change their hiring or firing policies remains unanswered in this research paper. We conclude that companies that introduce new technologies do not show any differences in training, at least for the people who work with these technologies. Evidently, companies make use of various forms of CVET, often including mandatory courses on the use of new technologies. Thus, CVET benefits those employees who are affected by the introduction of technology at their workplaces. This can partially reduce the negative consequences of automation, such as the risk of unemployment when new technologies are introduced. This is based on the assumption that learning occurs in educational settings, such as courses and self-directed learning periods, and that this knowledge is subsequently applied effectively in professional contexts (Ford et al. 2018). Actions in companies are of great importance in the digitalization of the economy and work. In particular, if CVET measures are planned and supported, this can be used as an instrument to secure or increase the productivity of companies and thus also the employability of employees with predominantly upper secondary vocational education, especially in times of changing working environments due to technological developments.

## Appendix

See Tables 7, 8

### Graphical representations

See Figs. 1, 2, 3, 4[3].

**Table 7** Conversions and variable labels

| Original variables | Transformations |
|---|---|
| **Qualifications:** | **Qualifications:** |
| - Apprenticeship—professional in-company training<br>- Vocational education (vocational/trading school) | - Upper secondary vocational education (DQR4-5) |
| - Professional school, technical school or college for master craftspersons; vocational school or professional academy<br>- Bachelor at a university (of applied sciences) | - UAS bachelor (DQR6) |
| - University of applied sciences degree, diploma, master<br>- University degree, diploma, magister degree, state examination, master degree | - UAS master degree/university degree (DQR7) |
| **Technologies:** | **Technologies:** |
| - Email, communication and scheduling: email programs, messenger services, intranet, agile working.Smartphones/cell phones/tablets: computers, smartphones, cell phones, tablets, lap-top, mobile deviceWeb meetings: web meetings, online conferences, telephony | - Easy-to-use software/mobile devices |
| - Collaboration software and clouds: collaboration software, team coordination, cloud computingOperating systems, databases and standard software: operating systems, office, graphics, animation, standard software, databases, AI/ML, programming environment, Business management software: business processes, accounting, controlling, BI, sales, purchasing, production, warehousing and human resources | - Complex software: Computer-aided software that requires a IT-learning process |
| - Traditional production equipment: manufacturing equipment, scanners, cash registers, packing machines, tools, machines | - Classical production machines |
| - Modern production resources: robotics, automation, control systems, 3D printing | - Modern (digital) production machines: that require an IT-learning process |

[3] As the partial effects of base and interaction effects are listed separately in Models 1b, 2b, 3b and 4b, the combined effects of base and interaction effects were calculated and graphically displayed for better interpretation and comparability. As an example, the base effects of UAS bachelor's degree (1.179) and complex software (1.478) in Model 1b are multiplied by their interaction effect (1.139) to obtain the value of 1.984 shown in Fig. 1. This indicates the relative probability of UAS bachelor's graduates who work with complex software in relation to employees with upper secondary vocational education who work with simple software (reference category) to participate in internal courses. As a result of this calculation, the confidence interval and significance of the interaction effects may also change. This has no influence on the interpretation of the results and our conclusion. Each line thus shows the relative probability to the reference category of participating in the respective form of CVET with the corresponding 5% confidence interval. The corresponding base effects of the respective variables from the tables have been labeled accordingly in the graph.

**Table 8** Questions and responses options

| Questions | Response options |
| --- | --- |
| 1. Has new technology been introduced in your workplace in the last two years? | A: Yes<br>B: No<br>C: I cannot/do not want to answer |
| 2. Please, name the technology or application that has most changed the way you work or what you do in the last two years | Open Answer |
| 3. Which of the following opportunities did you use to acquire the skills and competencies needed for the new technology you just mentioned? | A: internal further education courses<br>B: external training courses<br>C: self-study and trial and error<br>D: Explanations from other people directly at the workplace |

Question 2 and 3 were only asked if question 1 was answered yes

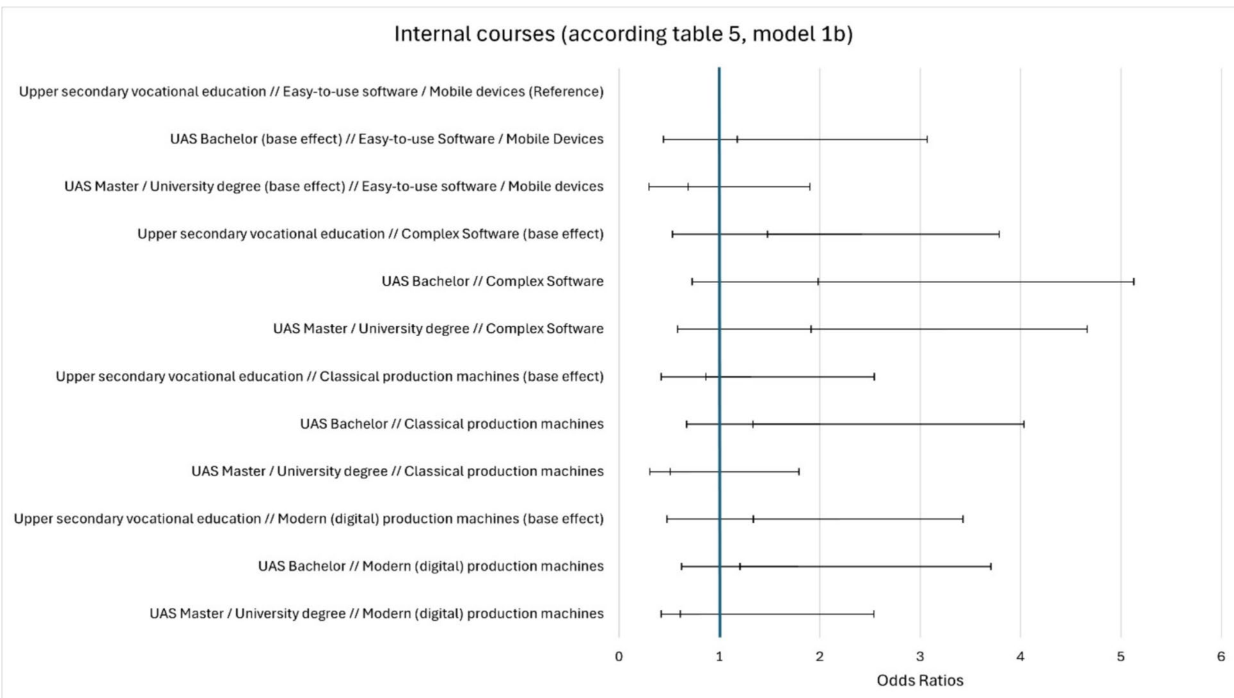


**Fig. 1** Base and interaction effects on participation in internal courses (displayed with 5% confidence interval)

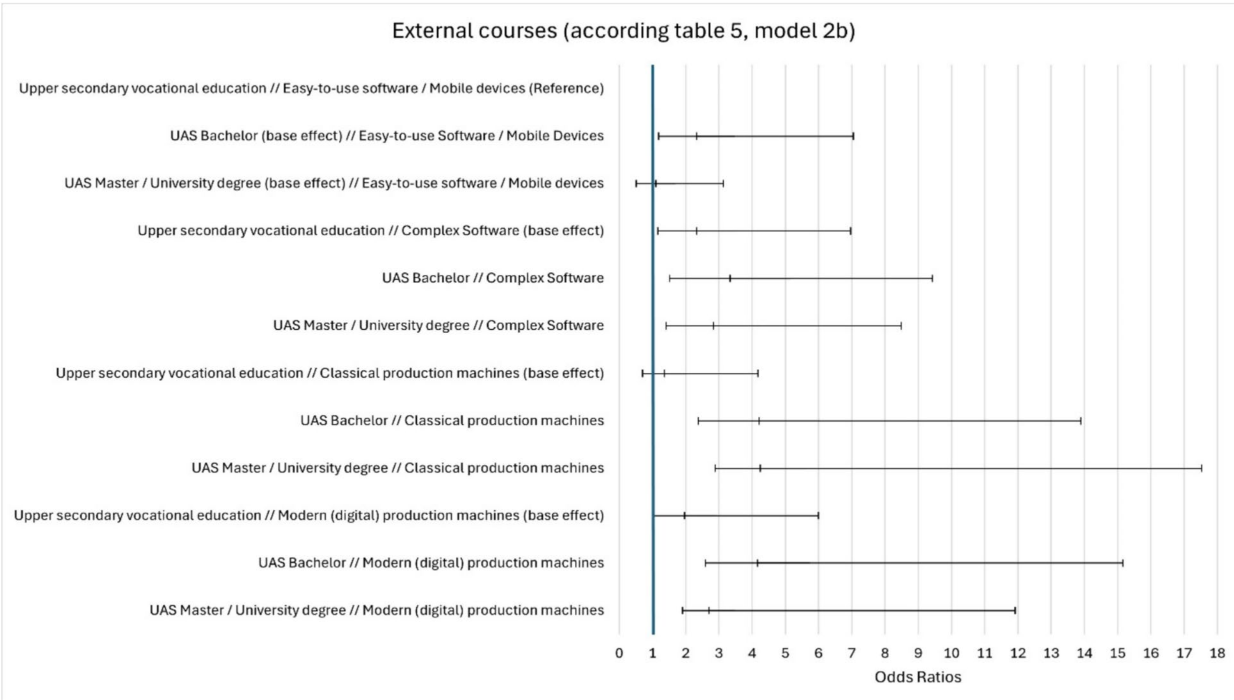


**Fig. 2** Base and interaction effects on participation in external courses (displayed with 5% confidence interval)

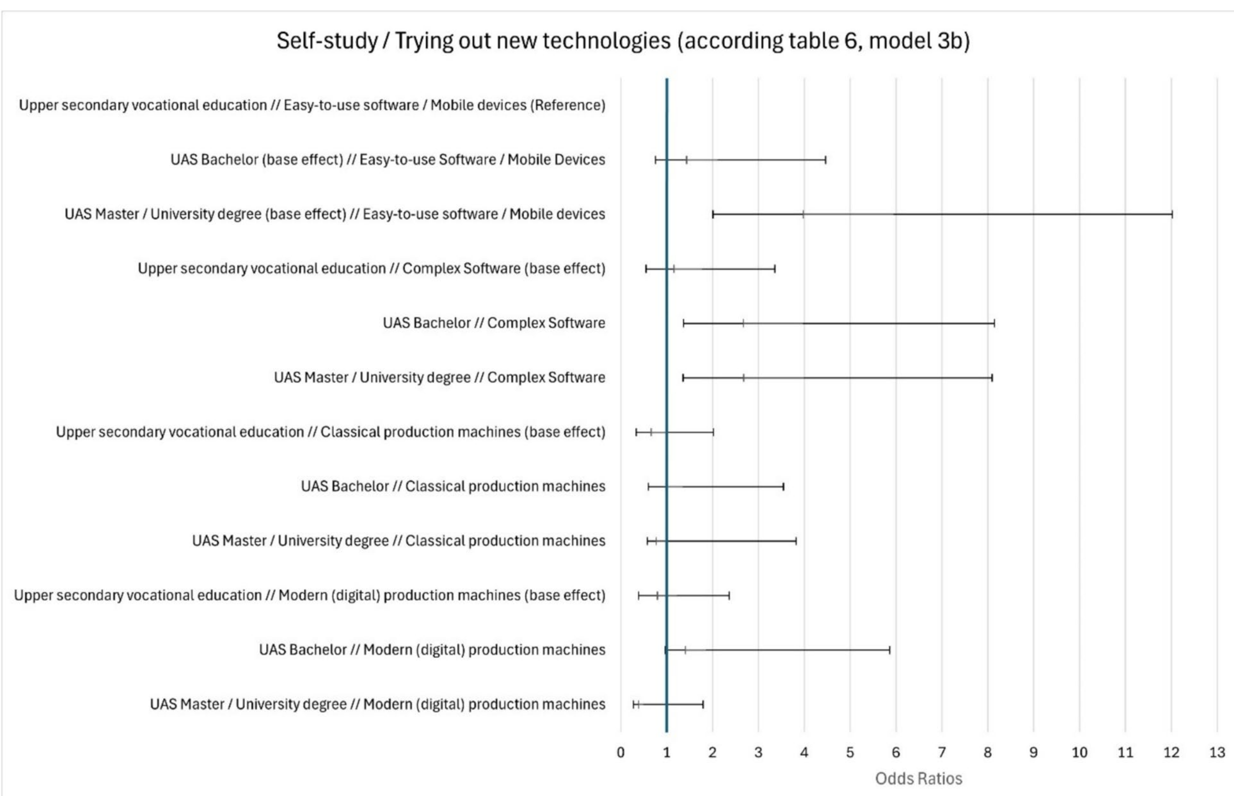


**Fig. 3** Base and interaction effects participation in self-study/trying out new technologies (displayed with 5% confidence interval)

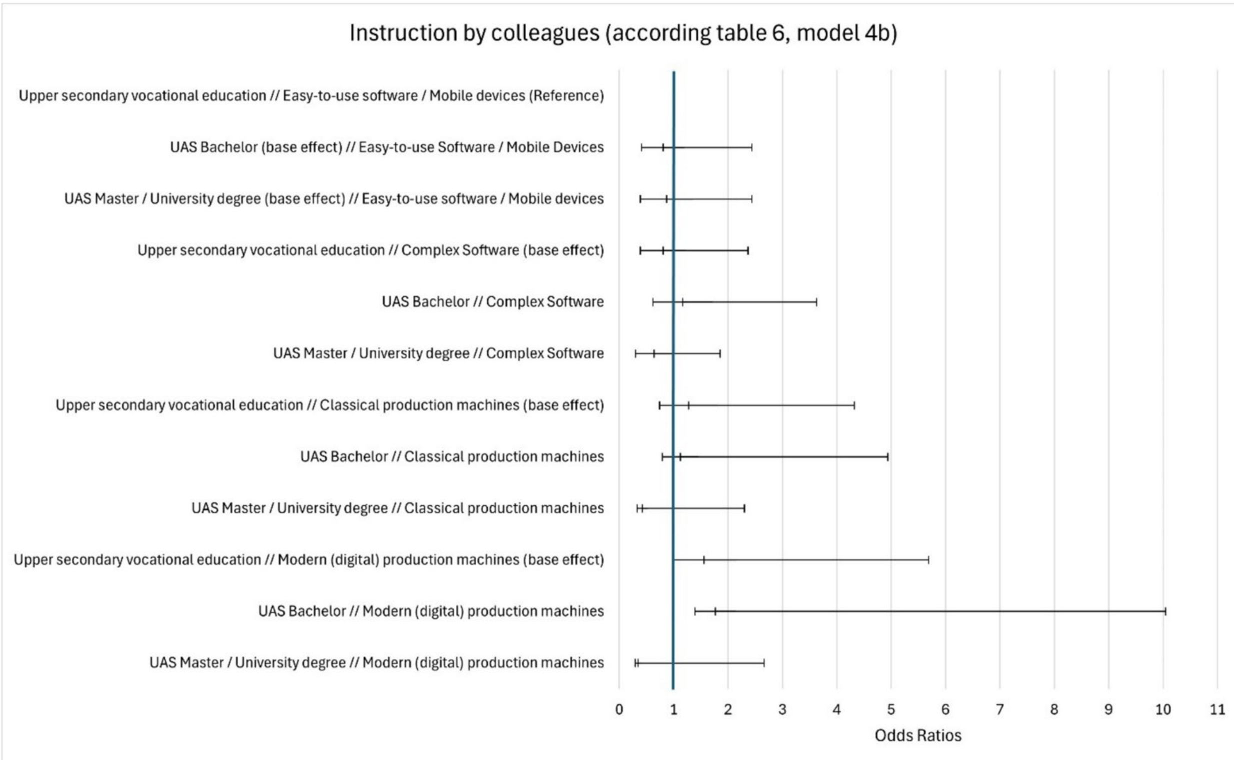


**Fig. 4** Base and interaction effects on participation in Instruction by colleagues (displayed with 5% confidence interval)

**Author contributions**
AS presented the research question, the basic theory, the design of the models and their evaluation as well as the first version of the manuscript. The subsequent revisions and improvements of the article were carried out in collaboration between AS and OS.

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**Data availability**
The data for this paper are social security data and are subject to data protection regulation, the data used cannot be made publicly available. They are kept at the Institute for Employment Research (IAB) in Nuremberg, Germany and can be accessed there.

## Declarations

**Ethics approval and consent to participate**
Not applicable.

**Consent for publication**
Not applicable.

**Competing interests**
The authors declare that they have no competing interests.

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**References**
Acemoglu, D., Restrepo, P.: Automation and new tasks: how technology displaces and reinstates labor. J. Econ. Perspect **33**(2), 3–30 (2019)
Albert, C., García-Serrano, C., Hernanz, V.: On-the-Job training in Europe: determinants and wage returns. Int. Labour Rev. **149**(3), 315–341 (2010)
Aldrich, J.H., Nelson, F.D.: Linear probability, logit and probit models (quantitative applications in the social sciences). Sage pub. Inc, London (1984)
Arntz, M., Gregory, T., Zierahn, U.: The risk of automation for jobs in OECD countries: A comparative analysis (OECD Social, Employment and Migration Working Paper No. 189) (2016)
Arrow, K.J.: Higher education as a filter. J. Public Econ. **2**, 193–216 (1973)
Asplund, R.: The provision and effects of company training: a brief review of the literature. Nordic J. Political Econ. **31**, 47–73 (2005)
Autor, D.H.: Work of the past, work of the future. AEA Papers Proc. **109**(May), 1–32 (2019)
Autor, D.H., Dorn, D.: The growth of low-skill service jobs and the polarization of the US labor market. Am. Econ. Rev. **103**(5), 1553–1597 (2013)
Autor, D.H., Levy, F., Murnane, R.J.: THE skill content of recent technological change: an empirical exploration. Q. J. Econ. **118**(4), 1279–1333 (2003)
Baethge-Kinsky, V.: Digitized industrial work: requirements, opportunities, and problems of competence development. Front. Sociol. **5**(33), 1–13 (2020)
Bäumer, T., Klieme, E., Kuger, S., Maaz, K., Roßbach, H., Stecher, L., Struck, O.: Education processes in life-course-specific learning environments. In: Blossfeld, H.-P., Roßbach, H.-P. (eds.) Education as a lifelong process The German National Panel Study. Springer, Wiesbaden (2019)
Bechmann, S., Tschersich, N., Ellguth, P., Kohaut, S., Baier, E., Florian, C.: Technical Report on the IAB Establishment Panel Wave 27 (2019). IAB FDZ-Methodenreport 01|2021, 1–43 (2021)
Becker, G.S.: Investment in Human capital: a theoretical analysis. J. Polit. Econ. **70**(5), 9–49 (1962)
Bellmann, L. Datenlage und Interpretation der Weiterbildung in Deutschland. Expertenkommission Finanzierung Lebenslagen Lernens. wbv, Bielefeld (2003)

Bereiter, C., Scardamalia, M.: Intentional learning as a goal of instruction. In: Resnik, L.B. (ed.) Knowing, Learning, and Instruction. Essays in Honor of Robert Glaser. Erlbaum, Hillsdale (1989)
Bessen, J., Goos, M., Salomons, A., Van Den Berge, W.: Automatic reaction: What happens to workers at firms that automate? Rev. Econ. Stat. **107**(1), 125–141 (2025)
Blossfeld, H.-P., Kilpi-Jakonen, E., Vono de Vilhena, D., Buchholz, S.: Is there a Matthew effect in adult learning? Results from a cross-national comparison. In: Schrader, J., Ioannidou, A., Blossfeld, H.-P. (eds.) Monetäre und nicht monetäre Erträge von Weiterbildung: Monetary and non-monetary effects of adult education and training. Springer, Wiesbaden (2020)
Boeren, E.: Adult education participation: The Matthew principle. Filosofija-Sociologija **20**(2), 154–161 (2009)
Bonin, H., Gregory, T., Zierahn, U.: Übertragung der Studie von Frey/Osborne (2013) auf Deutschland: Endbericht. ZEW-Kurzexpertise **57**, 1–44 (2015)
Bosch, G., Charest, J.: Vocational training and the labour market in liberal and coordinated economies. Ind. Relat. J. **39**(5), 428–447 (2008)
Brynjolfsson, E., McAfee, A.: The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W.W. Norton and Company, New York (2014)
Callanan, M., Cervantes, C., Loomis, M.: Informal learning. Wiley Interdiscipl. Rev. Cogn. Sci. **2**(6), 646–655 (2011)
Campaner, A., Heywood, J.S., Jirjahn, U.: Flexible work organization and employer provided training: evidence German linked employer-employee data. Kyklos **75**(1), 3–29 (2022)
Candy, P.C.: Self-direction for lifelong learning. Jossey-Bass, San Francisco (1991)
Dauth, C.: Regional discontinuities and the effectiveness of further training subsidies for low-skilled employees. ILR Rev. **73**(5), 1147–1184 (2020)
Decius, J., Schaper, N., Seifert, A.: Work characteristics or workers' characteristics? An input-process-output perspective on informal workplace learning of blue-collar workers. Vocat. Learn. **14**, 285–326 (2021)
Dehnbostel, P.: Betriebliche Bildungsarbeit. Kompetenzbasierte Aus- und Weiterbildung im Betrieb. Schneider Verlag, Hohegehren (2010)
Dengler, K., Matthes, B.: The impacts of digital transformation on the labour market: substitution potentials of occupations in Germany. Technol. Forecast. Soc. Chang. **137**, 304–316 (2018)
Dieckhoff, M.: Does it work? The effect of continuing training on labour market outcomes: a comparative study of Germany, Denmark, and the United Kingdom. Eur. Sociol. Rev. **23**(3), 295–308 (2007)
Doeringer, P.B.: Determinants of the structure of industrial type internal labor markets. ILR Rev. **20**(2), 206–220 (1967)
Dütsch, M., Struck, O.: Employment trajectories in Germany: do firm characteristics and regional disparities matter? J. Labour. Market Res. **47**(1–2), 107–127 (2014)
Ehlert, M.: Who benefits from training courses in Germany? Monetary returns to non-formal further education on a segmented labour market. Eur. Sociol. Rev. **33**(3), 436–448 (2017)
European Commission: A Memorandum of Lifelong Learning. Commission of the European Communities, Brüssel (2000)
Federal Ministry of Education and Research: What is a Qualifications Framework?. https://www.dqr.de/dqr/en/the-dqr/what-is-a-qualifications-framework/what-is-a-qualifications-framework_node.html (Accessed on 17.03.2025)
Ford, J.K., Baldwin, T.T., Prasad, J.: Transfer of training: the known and the unknown. Annu. Rev. Organ. Psych. Organ. Behav. **5**(1), 201–225 (2018)
Frey, C.B., Osborne, M.A.: The future of employment: how susceptible are jobs to computerisation? Technol. Forecast. Soc. Chang. **114**, 254–280 (2017)
Gegenfurtner, A., Vauras, M.: Age-related differences in the relation between motivation to learn and transfer of training in adult continuing education. Contemp. Educ. Psychol. **37**(1), 33–46 (2012)
Genz, S., Bellmann, L., Matthes, B.: Do German works councils counter or foster the implementation of digital technologies? Jahrbücher Für Nationalökonomie und Statistik **239**(3), 523–564 (2019)
Goos, M., Manning, A.: Lousy and lovely jobs: the rising polarization of work in britain. Rev. Econ. Stat. **89**(1), 118–133 (2007)
Goos, M., Manning, A., Salomons, A.: Explaining job polarization: routine-biased technological change and offshoring. Am. Econ. Rev. **104**(8), 2509–2526 (2014)
Illeris, K.: Towards a contemporary and comprehensive theory of learning. Int. J. Lifelong Educ. **22**(4), 396–406 (2003)
Janssen, S., Leber, U., Arntz, M., Gregory, T., Zierahn, U.: Betriebe und Arbeitswelt 4.0: Mit Investitionen in die Digitalisierung steigt auch die Weiterbildung. IAB-Kurzbericht **26**, 1–8 (2018)
Josten, C., Lordan, G.: Robots at work: Automatable and Non Automatable jobs. IZA DP No. 12520. IZA Institute of Labor Economics. (2019)
Kohl, J.: Teilnehmende und Teilnahme an Weiterbildung. In: Widany, S., Reichart, E., Christ, J., Echarti, N. (eds.) Trends der Weiterbildung. DIE-Trendanalyse 2021, pp. 209–248, wbv, Bielefeld (2021)
Kohler, U., Kreuter, F.: Datenanalyse mit Stata. Allgemeine Konzepte der Datenanalyse und ihre praktische Anwendung (5th ed.). De Gruyter, Oldenburg (2017)
Konings, J., Vanormelingen, S.: The impact of training on productivity and wages: firm-level evidence. Rev. Econ. Stat. **97**(2), 485–497 (2015)
Lee, J., Desjardins, R.: Inequality in adult learning and education participation: the effects of social origins and social inequality. Int. J. Lifelong Educ. **38**(3), 339–359 (2019)
Lehmer, F., Matthes, B.: Auswirkungen der Digitalisierung auf die Beschäftigungsentwicklung in Deutschland. IAB - Aktuelle Berichte **5**, 1–9 (2017)
Li, J.H., König, M., Buchmann, M., Sacchi, S.: The influence of further education on occupational mobility in Switzerland. Eur. Sociol. Rev. **16**(1), 43–65 (2000)
Liable, M.-C., Anger, S., Baumann, M.: Personality traits and further training. Front. Psychol. **11**(510537), 1–20 (2020)
Lischewski, J., Seeber, S., Wuttke, E., Rosemann, T.: What influences participation in non-formal and informal modes of continuous vocational education and training? An analysis of individual and institutional influencing factors. Front. Psychol. **11**, 1–19 (2020)
Lutz, B., Köhler, C., Grünert, H., Struck, O.: The German model of labour market segmentation – tendencies of change. Socio-Économie du Travail n28 (Économies et Sociétés, tome XLI), 1057–1088 (2007)
Marsick, V.J., Watkins, K.: Informal and Incidental Learning in the Workplace. Routledge, London (2016)
Mayer, K.U., Solga, H.: Skill formation interdisciplinary and cross-national perspectives. Cambridge University Press, New York (2008)
Michaelis, C., Busse, R., Seeber, S., Eckelt, M.: Nachschulische Bildungsverläufe in Deutschland. Schulentlassene zwischen institutionalisierten Idealwegen und schwierigen Umwegen. Berufsbildung, Arbeit und Innovation 72. wbv: Bielefeld. (2022)
Nedelkoska, L., Quintini, G.: Automation, skills use and training OECD Social. Employment and Migration Working Papers **202**, 1–124 (2018)
Ohlert, C., Giering, O., Kirchner, S.: Who is leading the digital transformation? Understanding the adoption of digital technologies in Germany. N. Technol. Work. Employ. **37**, 445–468 (2022)
Pfeifer, C., Janssen, S., Yang, P., Backes-Gellner, U.: Effects of training on employee suggestions and promotions: evidence from personnel records. Schmalenbach Bus. Rev. **65**(3), 270–287 (2013)
Ramos, C.R., Harris, R.H.: Training and its benefits for individuals: what form, what for and for whom? Evidence from the literature and implications for government-sponsored training. Int. J. Learn. Ann. Rev. **18**(6), 371–382 (2012)
Rand, O.A.M., Henretta, J.C.: Cumulative processes in the life course. In: Elder, G.H., Jr., Giele, J.Z. (eds.) The craft of life course research. The Guilford Press, New York (1999)
Rausch A.: Erleben und Lernen am Arbeitsplatz in der betrieblichen Ausbildung. Wachsmann, Münster (2012)
von Rosenbladt, B., Bilger, F., Much, P.: Weiterbildungsbeteiligung in Deutschland. Eckdaten zum BSW-AES. München: TNS Infratest Sozialforschung (2008)
Rubenson, K., Desjardins, R.: The impact of welfare state regimes on barriers to participation in adult education. Adult Educ. Q. **59**(3), 187–207 (2009)
Ruf, K., Mackeben, J., Haepp, T., Wolter, S., Grunau, P.: LPP—linked personnel panel 1819 quality of Work and economic success: longitudinal study in german establishments (data documentation on the fourth wave). FDZ-Datenreport **11**(2020), 1–245 (2020)
Seyda, S.: Digitale Lernmedien beflügeln die betriebliche Weiterbildung Ergebnisse der zehnten IW-Weiterbildungserhebung. IW-Trends **48**(1), 79–94 (2021)
Slaten, C.D., Rose, C.A., Elison, Z.M., Ming Ming, C.: Understanding the connection between youths' belonging, resilience and self-regulatory learning. Educ. Child Psychol. **36**(2), 91–105 (2019)

Sonntag, K.H., Schaper, N.: Weiterbildungsverhalten. In: Frey, D., Rosenstiel, L.V. (eds.) Enzyklopädie der Psychologie, pp. 573–648. Hogrefe, Göttingen (2007)
Taylor, P., Urwin, P.: Age and participation in vocational education and training. Work Employ Soc. **15**(4), 763–779 (2001)
van Laar, E., van Deursen, A.J.A.M., van Dijk, J.A.G.M., de Haan, J.: The relation between 21st-century skills and digital skills: a systematic literature review. Comput. Hum. Behav. **72**, 577–588 (2017)
Wang, B., Liu, Y., Qian, J., Parker, S.K.: Achieving effective remote working during the COVID-19 pandemic: a work design perspective. Appl. Psychol. Int. Rev. **70**(1), 16–59 (2021)
Wenzelmann, F., Müller, N.: Berufliche Weiterbildung aus Sicht der Individuen. Eine Bilanz von Aufwand und Nutzen. BiBB-Rep. **4**, 1–16 (2018)
Wooldridge, J.M.: Introductory econometrics: a modern approach, 5th edn. South-Western Cengage Learning, Boston (2013)
Zeyer-Gliozzo, B.: Returns to formal, non-formal and informal training for workers at risk of automation. Ruhr Econ. Papers **857**, 1–43 (2020)

## Publisher's Note