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Tasks as a Link Between Technology Introduction and Continuing Training: Evidence of a Mediating Mechanism in Firms

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ABSTRACT

New technology is changing the skills that employers demand and the tasks that employees perform. Technological change is therefore increasing the need for continuing vocational training. However, little is known about the association between technology introduction, employees' job tasks and continuing training participation in firms. Employees' job tasks may mediate the relationship between technology introduction and continuing training participation. As tasks are distributed unequally among employees, tasks may reinforce inequality in continuing training. This study uses German firm-level data (BIBB Training Panel, $n = 1057$) to identify such a mediating effect. The results show that the association of technology, tasks and continuing training varies depending on the form of continuing training. Technology introduction does directly affect informal continuing training rates, but not course-based continuing training rates. Nevertheless, technology introduction does increase the frequency of all types of tasks in firms. Moreover, manual tasks have a direct negative effect on the course-based continuing training rates. The results suggest that manual tasks mediate the relationship between technology introduction and course-based continuing training. Also, the results highlight the importance of tasks for reinforcing inequalities in continuing training participation in times of technological change.

1 | Introduction

In times of technological change, new (digital) technology occurs that alters the current and future work environment in Europe (Autor et al. 2003; Bachmann et al. 2019; Fernández-Macías et al. 2023; Goos and Manning 2007; Heß et al. 2023; Minardi et al. 2023). Therefore, technological change is accompanied by changes in tasks as well as in skill and qualification requirements—eventually leading to employment reallocations (Arntz et al. 2017; Bachmann et al. 2019; Fernández-Macías et al. 2023; Hardy et al. 2018). The academic and political discourse, especially in the European Union, praises continuing vocational training—that is, learning after entering the labour market (CEDEFOP 2023)—as the key to adapting employees to these

changes (Biagi and Sebastian 2020; Blossfeld et al. 2020; Heß et al. 2023; Lammers et al. 2023; Offerhaus et al. 2016). Several empirical studies point out a positive relationship between technological change indicators and continuing training participation in German firms (Baum and Lukowski 2022; Lukowski et al. 2021; Mohr et al. 2016; Müller 2024).

Training is not only a means of adapting to change, but it also has the potential to equalise educational opportunities (Offerhaus et al. 2016). However, participation in continuing training is very unevenly distributed and still highly dependent on previous educational opportunities (Blossfeld et al. 2020): low-skilled employees are less likely to participate in continuing training in many European countries (Martin and Rüber 2016;

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Ramos and Harris 2012) and especially in Germany (e.g., Offerhaus et al. 2016; Schindler et al. 2011). Moreover, for employees with low-skilled tasks, research oftentimes shows no (positive) relationship between technological change indicators and continuing training participation (e.g., Baum and Lukowski 2022; Wotschack 2020a, 2020b). The unequal distribution of job tasks might be a reason for such a pattern and the general unequal distribution of continuing training.

Employees differ greatly in the types of job tasks they more frequently perform (Autor and Handel 2013; Autor et al. 2003; Rohrbach-Schmidt 2019). For example, routine tasks are more common for low-skilled employees, while analytical tasks are more common for high-skilled employees. Furthermore, the type of job tasks employees perform is strongly related to their continuing training participation: interactive and analytical tasks are typically positively correlated with training participation, while routine and manual tasks are negatively correlated (Ehlert 2020; Görlitz and Tamm 2016b; Heß et al. 2019, 2023; Kleinert and Wölfel 2018; Lukowski et al. 2021). Therefore, tasks can act as a reinforcing inequality dimension for the already unequally distributed participation in continuing training.

As technological change is altering the tasks employees perform (e.g., Acemoglu and Autor 2011; Autor et al. 2003; Fernández-Macías et al. 2022), these changes in tasks and the need to adapt are a possible explanation for the association between technology and continuing training (e.g., Ehlert 2020; Mohr et al. 2016; Wotschack 2020a). Consequently, technology might not have a direct impact on continuing training participation in firms. Rather, tasks mediate the effect of technology on continuing training participation. This mediation is a frequently made theoretical assumption (e.g., Ehlert 2020; Heß et al. 2019; Kleinert and Wölfel 2018; Mohr et al. 2016) but—to the author's knowledge—has never been specifically tested.

The aim of the article is to test the mediation assumption in order to understand why certain employee groups participate less frequently in continuing training than others and to reveal the extent to which tasks influence this relationship. By focusing on further explaining the link between technology, tasks and continuing training, this article aims to advance the understanding of this complex relationship, which has the potential to reinforce social inequalities. Employees who are not participating in continuing training might have a harder time adapting to the changing work environment and are in danger of being left behind. Illuminating the mechanisms of the relationship between technology, tasks and training might help to better understand the existing inequalities in continuing training and to prepare all employees for the changing world of work.

Research on technological change and continuing training tends to focus on non-formal continuing training (i.e., relatively short training courses or seminars that do not lead to an official degree, but certificates are possible [Bilger et al. 2017]), while it tends to neglect informal continuing training (i.e., learning outside formal structures, such as self-regulated learning with books, computers or presentations [Bilger et al. 2017]). However, especially informal training plays an important role in the context of technological change (Bilger et al. 2017; Ehlert 2020) and general human capital development (Grip and de 2024).

This article looks at both types of continuing training. Firm-level panel data from Germany and structural equation models

(SEMs) are used to answer the question of whether employees' tasks mediate the relationship between technology introduction in firms and their participation in different types of continuing training. Two separate SEMs analyse this mediating relationship for (1) firm-sponsored course-based continuing training (i.e., similar to non-formal continuing training) and (2) firm-sponsored informal continuing training (i.e., on-the-job training, information events and self-directed learning, all of which the employer is aware of).

2 | Literature and Theory

2.1 | Continuing Training Determinants

Continuing training is a heterogeneous term that describes different types of intentional adult learning (Bilger et al. 2017; Lischewski et al. 2020). Continuing vocational training aims to improve, adapt or maintain employees' skills (Bellmann and Leber 2019; Offerhaus et al. 2016). In the case of firm-sponsored continuing training—the focus of this article—the employer covers all or parts of the direct (e.g., participation fees) or indirect (e.g., opportunity costs) training costs (Bilger et al. 2017). However, it is important to bear in mind that continuing training measures and definitions vary considerably between countries (Ebner and Ehlert 2018). Also, the degree of regulation, governance and financing of continuing training for employees varies strongly between countries. Coordinated market economies such as the Nordic states and Germany are commonly characterised by high state involvement, while liberal economies like the United Kingdom usually have low state involvement and are highly employer-driven (Thelen 2014). Germany represents a special case of a coordinated market economy in regard to vocational training due to high firm involvement (Thelen 2014). Germany's continuing training system has a comparably low degree of state and union regulation and is mainly organised by employers and employees (Allaart et al. 2009). Hence, the majority of continuing training in Germany is sponsored by firms (Bassanini et al. 2007; Dobischat et al. 2019; Dohmen and Cordes 2019).

Depending on the data source, the definition of continuing training and the reference time point, between 55% and 88% of firms in Germany sponsored continuing training in the last few years (Jost 2022; Schönfeld and Thiele 2023; Seyda and Placke 2020; Weis and Mohr 2023). With these numbers in the years before the Covid-19 pandemic, Germany ranked in the (upper) midfield compared to other European countries—not only in regard to firms offering training but also in hours spent on training and employee participation in such training (Schönfeld and Thiele 2018; Thiele and Schönfeld 2018). However, according to the Continuing Vocational Training Survey (CVTS), firm-sponsored continuing training activities in Germany remained relatively stable during the Covid-19 pandemic. As a result, Germany was able to improve its position relative to other European countries (Schönfeld and Thiele 2023).

The likelihood of participating in continuing training depends on individual characteristics such as qualifications (e.g., low-skilled or mismatched employees are less likely) or the learning biography, as well as on job (e.g., occupational status, contract type) and firm characteristics (e.g., employees in

larger firms are more likely) (e.g., Offerhaus et al. 2016; Schindler et al. 2011; Lischewski et al. 2020). Other important firm characteristics include the sector, formalised HR practices and technological or organisational developments (e.g., Offerhaus et al. 2016; Wotschack 2020b; Lischewski et al. 2020).

Accordingly, participation in continuing training depends on self-selection and external selection (Blossfeld et al. 2020; Kaufmann and Widany 2013; Offerhaus et al. 2016; Lischewski et al. 2020), with employers acting as central gatekeepers (Ehlert 2017). Especially in Germany, the low state regulation and high dependency on employers contribute to the pattern that training mostly goes to those employees who are higher valued by the employer (Roosmaa et al. 2019), which contributes to high continuing training inequalities. Therefore, the focus of this article is on the participation in firm-sponsored continuing training in Germany.

An often-cited explanation for participation and provision of continuing training—as well as the appearance of continuing training inequalities—is human capital theory (Becker 1962), according to which all investments in employees (physical and non-physical) that could increase future productivity are investments in human capital, for example, continuing training. Investment in human capital is analysed in the same way as investment in other forms of capital (Becker 1962). A related explanation, focusing more on the firms' perspective, but with similar assumptions about human capital (Foss 2008), is transaction cost theory—the costs of transferring rights of goods or services (Williamson 1979).

In both theories, employers have to weigh up the immediate direct and indirect costs of continuing training against the future benefits (e.g., increased productivity). Employers will only invest if the benefits outweigh the costs (Becker 1962). However, costs and benefits are not purely monetary (Balog and Demidova 2021; Becker 1994; van Loo and Rocco 2004), actors are not fully rational and maximising income or productivity is not their only goal¹ (Balog and Demidova 2021), and external factors can alter cost–benefit analyses (Becker 1994).

2.2 | Technology and Continuing Training

The technological change—automation of work processes through (digital) technology (Seegers and Ehmann 2021)—is accompanied by changes in tasks, skills and qualification requirements (Arntz et al. 2017; Bachmann et al. 2019; Fernández-Macias et al. 2023; Hardy et al. 2018). In this context, recent research has focused mainly on digital technology (hereafter just technology) and especially on computer-controlled technology (e.g., Autor et al. 2003; Fernández-Macias et al. 2023; Haslberger 2022; Seegers and Ehmann 2021). Such computer-controlled technology encompasses among other technology for digital production processes and all kinds of ICT (information and communication technology).

Changes in such technology are possibly leading to changes in firms (Gerlach et al. 2002), for example, technological change oftentimes requires different human capital, such as new knowledge and creativity (Balog and Demidova 2021). Continuing training supplies employers with appropriately skilled employees (e.g., Bellmann and Leber 2019). Therefore, one reason for the positive relationship between technology and

continuing training is that newly introduced technology requires certain employees to adapt through training, as they feel the need to adapt their skills, or because the employer sees the need for employees to adapt (Gerlach et al. 2002; Käßplinger 2016; Lischewski et al. 2020). So, continuing training can be an important means of coping with changes at the workplace due to technology. This makes continuing training more valuable for employers, which increases the benefits of continuing training and makes investments more likely.

Those cost–benefit analyses are not static but adapt to environmental changes, for example, technological change (Becker 1994). Without training, employees may find it more difficult to adapt to technological change, which could negatively impact their productivity. Consequently, when technology changes, the cost–benefit analysis could become positive—with the benefits of training outweighing the costs—and employers might offer more continuing training to all employees, leading to less inequalities. Empirically, technology introduction, use or investments are positively related to participation in, provision of or investments in continuing training in firms (Baum and Lukowski 2022; Gerlach et al. 2002; Lukowski et al. 2021; Mohr et al. 2016; Müller 2023). Also, employees who agree that continuing training helps them adapt to changes in technology participate more in continuing training (Lischewski et al. 2020). Consequently, it is assumed that:

H1. *Technology introduction increases continuing training in firms.*

The directions of the relationships between continuing training, technology and tasks (discussed in the next sections) are still debated. Alternatives to the hypotheses presented are discussed at the end of the chapter.

2.3 | Technology and Changes in Tasks

Since the 1990s, there have been various theoretical explanations of how technology affects wage structures and inequalities in the labour market by changing firms' skill and task requirements. To explain changes in task requirements, the task-based approach (Autor et al. 2003) and the routine-biased technological change (RBTC) hypothesis (Goos et al. 2014) were introduced. These two theoretical approaches focus on employees' tasks rather than skills to explain how technology affects employees. Job tasks refer to the activities that employees perform to produce output. Skills, on the other hand, are the abilities that employees possess in order to perform these tasks (Acemoglu and Autor 2011; Biagi and Sebastian 2020). Originally, Autor et al. (2003) categorised tasks based on two axes: routine versus non-routine tasks and cognitive versus manual tasks. This resulted in four groups: (1) non-routine cognitive, for example, medical diagnosis, managing others and complex communication; (2) non-routine manual, for example, janitorial and craft services; (3) routine manual, for example, sorting and repetitive assembly; (4) routine cognitive, for example, calculations and record keeping.

The main takeaway from the task-based approach and the RBTC hypothesis is that routine manual tasks and routine cognitive tasks follow formalised rules and are programmable and codifiable. Therefore, such routine tasks tend to be replaceable by technology. If the replacements are implemented, routine tasks will decrease,

as will the need for employees to perform them (Autor et al. 2003; Autor 2015; Goos et al. 2014). In contrast, technology complements non-routine cognitive tasks, which follow less formalised rules and are more difficult to programme. Technology helps employees to perform these tasks rather than replacing them, thereby increasing the labour demand for these tasks and the need of employees performing such tasks (Autor et al. 2003; Autor 2015; Goos et al. 2014). Finally, technology has only a little effect on the labour input of non-routine manual tasks (Autor et al. 2003; Autor 2015; Goos et al. 2014).

The initial categorisation by Autor et al. (2003) has been extended by several authors. Different operationalisations of the original tasks as well as new parallel or additional dimensions on the individual level, such as work autonomy or work tools, have been suggested (e.g., Autor and Dorn 2013; Fernández-Macías and Bisello 2022; Haslberger 2022; Sebastian and Biagi 2018). Still, the differentiation into routine/non-routine and cognitive/manual tasks is the basis of many studies looking at the influence of technological change on labour. Those studies continue to find that technology increases cognitive tasks, such as social interaction, communication and other non-linear work (Autor et al. 2003; Danuser and Kendzia 2019; Fernández-Macías et al. 2023; Hardy et al. 2018; Haslberger 2022; Sebastian and Biagi 2018; Spitz-Oener 2006). Autor et al. (2003) did not expect technology to affect manual tasks. However, other studies show that manual tasks are decreasing (Hardy et al. 2018).

For routine tasks, results are mixed: some show that routine tasks are substituted by technology (Autor et al. 2003; Sebastian and Biagi 2018; Spitz-Oener 2006), others find that overall employment structures are becoming less routine, while jobs themselves become more routine (Fernández-Macías et al. 2022). Others show that trends in routine intensity are conflicting: as complexity increases, routine decreases and vice versa—depending on the occupation (Haslberger 2022). Furthermore, a decrease in routine tasks or less routine tasks is more common in Western European countries than in Eastern European countries (Biagi and Sebastian 2020; Hardy et al. 2018). In summary, after a new technology is introduced, it is likely that the share of routine tasks is decreasing in German firms.

However, this overall decrease in routine tasks does not imply a decrease in such tasks for every employee, as tasks are unequally distributed among employees and depend on skill levels (Autor and Handel 2013; Autor et al. 2003; Friedrich 2023; Hardy et al. 2018; Rohrbach-Schmidt 2019). Oftentimes, low-skilled jobs are associated with replaceable routine manual tasks, while high-skilled jobs are associated with the (non-routine) cognitive tasks, which are less likely to be replaced (Autor and Handel 2013; Autor et al. 2003; Friedrich 2023; Hardy et al. 2018; Rohrbach-Schmidt 2019). With that, technological change is contributing to inequalities in the labour market.

This article adopts a categorisation based on the assumptions of Autor et al. (2003) and the RBTC hypothesis (Goos et al. 2014), distinguishing between tasks that are decreasing due to replacement tendencies, those tasks that are increasing due to complementarity with machines and computers and those tasks that are unaffected by technology. However, it also incorporates some adaptations: 1) *routine* manual and cognitive tasks (hereafter *routine tasks*) are repetitive and are likely to be replaced by technology; 2) non-routine *manual* tasks are

non-repetitive (hereafter *manual tasks*) and are neither replaced nor complemented by technology; 3) *interactive* and 4) *analytical* tasks, which are measuring the non-routine cognitive dimension, are separated, as they are measuring two different aspects of non-routine cognitive tasks. These tasks tend to be complemented by technology. Thus, the following hypotheses are proposed:

H2a. *Technology introduction decreases the routine tasks in firms.*

H2b. *Technology introduction does not affect the manual tasks in firms.*

H2c. *Technology introduction increases the interactive tasks in firms.*

H2d. *Technology introduction increases the analytical tasks in firms.*

2.4 | Tasks and Continuing Training

Employers should provide support for their employees to adapt to technological change and the expansion and creation of new tasks (Acemoglu and Restrepo 2018, 2019; Biagi and Sebastian 2020; Heß et al. 2023; Lammers et al. 2023) as current skills do not always match future requirements and employees feel the need to adapt (Acemoglu and Restrepo 2019; Heß et al. 2019). Part of these changes is that non-routine cognitive tasks—interactive or analytical—are becoming more important in the labour market, while certain routine tasks are declining (Fernández-Macías et al. 2022; Hardy et al. 2018; Haslberger 2022; Sebastian and Biagi 2018). These observed changes in the labour market are supporting the assumptions of **H2a/b/c/d**, but have not been researched or tested at the firm level.

Continuing training might help to cope with these changes (Görlitz and Tamm 2016b) in the labour market and inside firms. Furthermore, due to the increasing demand for non-routine cognitive tasks that are complemented by technology (i.e., analytical and interactive tasks), human capital investments should aim at producing skills to perform these tasks (Autor 2015; Danuser and Kendzia 2019). Consequently, one might expect that (induced by technology) for employees with increased analytical and interactive tasks, continuing training investments and needs should increase and training might become more beneficial, while for employees with increases in replaceable tasks—such as routine tasks—continuing training investments and needs should decrease and training might become less beneficial. For those employees with tasks that are less affected by technology—such as manual tasks—no or even lower training investments and needs might arise.

As tasks are unequally distributed (Autor and Handel 2013; Autor et al. 2003; Friedrich 2023; Hardy et al. 2018; Rohrbach-Schmidt 2019), this might contribute to increasing continuing training inequalities—as those employees with low-skilled jobs, who are rarely participating in continuing training (Offerhaus et al. 2016; Schindler et al. 2011), are also more often performing routine or manual tasks with lower training needs.

Moreover, task differences can oftentimes explain participation in continuing training better than differences in qualifications

or skills (Acemoglu and Pischke 1998, 1999; Ehlert 2020; Görlitz and Tamm 2016b). Employees with more routine or manual tasks are less likely to participate in continuing training, regardless of their skill or qualification level, whereas employees with many cognitive, analytical or interactive tasks participate significantly more (Ehlert 2020; Görlitz and Tamm 2016b; Heß et al. 2019, 2023; Kleinert and Wölfel 2018; Lukowski et al. 2021; Tamm 2018). Consequently, the following hypotheses are proposed:

H3a. *Routine tasks decrease the continuing training participation in firms.*

H3b. *Manual tasks decrease the continuing training participation in firms.*

H3c. *Interactive tasks increase the continuing training participation in firms.*

H3d. *Analytical tasks increase the continuing training participation in firms.*

To summarise: technology introduction affects the task structure, which in turn affects the continuing training rates. Thus, tasks might mediate (at least partially) the relationship between technology and continuing training in firms. Therefore, the fourth hypothesis is that:

H4. *Employees' tasks mediate the effect of technology introduction on continuing training in firms.*

The article analyses two types of continuing training: (1) course-based continuing training, which is similar to the definition of non-formal continuing training (Bilger et al. 2017); and (2) participation in informal continuing training settings (e.g., on-the-job training, information events or self-directed learning), which are reported by the firm and take place during the working time and/or are financed by the firm. Both types are analysed, as non-formal continuing training is the most common form, but a significant proportion of continuing training, particularly in the context of technological change, also takes place in informal settings (Bilger et al. 2017). No differences in the effects of tasks and technology on both types of continuing training are assumed, as both types of training have the aim to prepare employees for a changing work environment.

The analysis focuses on the relationships assumed in the hypotheses formulated above. However, depending on the hypothesis, reverse causality is possible. With regard to **H1**, the order of the association between technology and continuing training activities is still open to debate (e.g., Ehlert 2020; Gerlach et al. 2002; Heß et al. 2019; Janssen et al. 2018; Kleinert and Wölfel 2018). Particularly at the firm level, it is unclear what comes first, the new technology or training for an upcoming technology, or whether both occur simultaneously. For example, participation rates in continuing training could have a positive effect on the technology introduction in firms, because with newly trained employees, firms are able to more easily adapt a technology.

The common and stronger assumption in the literature is that technology changes the task content (e.g., Seegers and Ehmann 2021)—as **H2a/b/c/d** assumes. Nevertheless, it could be that the task structure of firms determines which kind of tasks firms are able to introduce (Bresnahan et al. 2002).

Görlitz and Tamm (2016a) find—against **H3a/b/c/d**—that the link between tasks and continuing training differences is not

driven by changes in firms, such as new technology. Moreover, continuing training might lead to changes in employees' tasks and not vice versa (Görlitz and Tamm 2016a; Nedelkoska and Quintini 2018; Tamm 2018; Zeyer-GlioZZo 2020).

If one of these possibilities is the case, the mediation assumption either does not hold or is reversed; for example, continuing training affects tasks, which then affect technology introduction. To counter these assumptions, a linear time sequence is assumed (Bullock et al. 1994): tasks (in t-1) mediate the effect of technology introduction (in t-2) on the continuing training rate (in t) in firms. Moreover, the influence of previous technology introduction on current technology introduction, and of previous continuing training and previous technology introduction on current continuing training, should be considered. In the next part, the operationalisation of the variables and the analytic strategy and model will be provided.

3 | Data and Method

3.1 | Data

The analysis builds on data from the 2017, 2018, 2019 and 2020 waves of the Federal Institute for Vocational Education and Training Establishment Panel on Training and Competence Development (BIBB Training Panel) (Friedrich et al. 2023). The panel was launched in 2011, with the aim of collecting information on around 3500–4000 firms and their vocational training activities annually. The disproportionately stratified random sample is representative of all firms based in Germany that have at least one employee subject to social insurance contributions. The stratification characteristics are size, sector and vocational education and training (VET) provision (Friedrich and Lukowski 2023). A total of 1200 firms participated in all four waves. Listwise deletion limits the sample to 1057 firms. This means there is high panel attrition, which may bias the data as only very specific firms participate in all waves.

3.2 | Operationalisation

3.2.1 | Continuing Training Rates

Two types of continuing training are distinguished: (1) course-based continuing training and (2) informal continuing training. The continuing training activities are surveyed after the firms have decided to provide continuing training. Firms should therefore only report continuing training that they consider beneficial.

In 2020, for (1) course-based continuing training, firms are asked whether 'employees [...] participated in 2019 in continuing training measures in the form of internal or external courses, seminars or training sessions which are financed in whole or in part by firms through release from work or cost absorption' and, if so, how many. Together with the total number of employees, the rate of *course-based continuing training participation* is calculated, ranging between 0 and 1.

In 2020, for (2) informal continuing training, firms are asked whether 'employees [...] participated in 2019 in other forms of continuing training such as on-the-job training, information events, or self-directed learning, which are financed in whole or

in part by firms through release from work or cost absorption' and, if so, how many. The rate of *participation in informal continuing training* is calculated, ranging between 0 and 1.

For the SEM analysis, a single indicator latent variable with a fixed reliability of 0.7 is used for both types of continuing training participation, where the measurement error (E) of the variance of the variable is multiplied by 0.3 (*1 minus the fixed reliability of 0.7*) (Savalei 2019).

To control for the previous continuing training rates in 2018 (surveyed 2019), for (1) course-based continuing training, the similarly calculated training rate is used. As the participation rate for (2) informal continuing training was only surveyed in wave 2020, it is included whether informal continuing training was provided (1) in 2018 (surveyed 2019) or not (0). Again, for the SEM analysis, a single indicator latent variable is calculated.

3.2.2 | Technology Introduction

The analysis focuses on the introduction of new technology in a firm to capture the changing nature of technology. Unfortunately, the data set encompasses only two broad measures on new technology introduction, which are not specifically focused on digital/computer technology. However, in both categories, advancements and the application of digital and computerised technology are very likely.

The introduction of technology in 2018 is surveyed by asking whether 'new ICT' and 'new production and control technology (PCT)' was introduced (1) in the previous year (2017) or not (0). Together, these two build the latent variable technology introduction (see Figure 1). To control for the influence of previous technology introduction, the influence of technology introduction in 2016 (surveyed 2017) is considered, which was surveyed and operationalised in the same way as the main independent variable.

3.2.3 | Employees' Job Tasks

Usually, tasks are measured through employee self-reports or occupational databases (Biagi and Sebastian 2020). The BIBB Training Panel measures tasks in a unique way, as it collects the firms' view on the kind of tasks its employees are performing. This reflects the employer's opinion on what their employees should be doing (similar to experts' opinions in occupational databases), which influences firms' decisions, as well as what employees actually do. This measurement of tasks has already been used in several other studies (Friedrich 2023; Lukowski et al. 2021; Mohr et al. 2016).

Employees' tasks are surveyed separately for employees with *low-, medium- and high-skilled jobs* in 2018 (surveyed in 2019) (same definition as for the continuing training participation). Four kinds of tasks can be distinguished: manual², routine³, interactive⁴ and analytical⁵. All were measured by two items. Firms rate whether a skill group never (1), rarely (2), sometimes (3), often (4) or very often (5) performs a task.

An unweighted index for the frequency of the tasks is calculated for the whole firm for each individual task by summing the information about the frequency for each skill group. The variables are then normalised to take a value between 0 and 1. The individual tasks frequency indices are used to define the latent variables of the employees' job tasks (see Figure 1). Since

the tasks in firms are interdependent (Friedrich 2023), their structural disturbances (D) are correlated with each other.

3.2.4 | Control Variables

Control variables should only be used if they influence all main variables. Therefore, only factors influencing participation in continuing training, technology introduction and job tasks (Friedrich 2023; Gerlach et al. 2002; Görlitz and Tamm 2016a; Schindler et al. 2011; Wotschack 2020a, 2020b) are included. As the goal of SEMs is theory testing, these control variables are only included in the robustness check and are limited to three important variables: (1) *firm size* (four categories), (2) the *economic sector* of the firm (eight categories) and (3) the *skill structure* of the firm (the share of employees in low-skilled (i.e., employees in jobs requiring no vocational qualification) and high-skilled jobs (i.e., employees in jobs requiring tertiary vocational qualification or equivalent)). The SEM model with control variables is displayed in Appendix (A).

3.3 | Analytic Strategy

The aim of the analysis is to test a mediation between technology introduction and continuing training rates in firms via employee tasks (see Figure 1). SEMs are useful for testing such potential causal relationships (Bollen et al. 2022; Pearl 2012) and are superior to Baron and Kenny (1986) stepwise regression approach for mediation analysis (Bollen et al. 2022; Iacobucci et al. 2007). Mediation analysis assumes causality of the relationship. SEMs (with nonexperimental data), as any other statistical method, do not per se prove a causal relationship, but they support its plausibility (Bollen et al. 2022; Bullock et al. 1994). The coefficients obtained can be interpreted as causal under certain conditions (Bollen et al. 2022; Pearl 2012). The relevant variables are included in a consecutive time order, and the influence of the previous year is considered, to avoid reverse causality, that is, a feedback model, and to meet the basic causality requirements (Bullock et al. 1994).

Figure 1 shows the mediation model. The variables in the ovals are latent variables consisting of more than one variable or, in the case of continuing training, are a single indicator latent variable with fixed measurement error terms (E) (see Operationalisation). The bold arrows show the direct associations between the variables as assumed in the mediation model, while the thin arrows are additional assumptions. The technology introduction in the previous year $t-3$ (2016) affects the probability of an introduction in the next year $t-2$ (2017), and the continuing training rate in $t-1$ (2018) affects the training rate in t (2019). In addition, the technology introduction in $t-3$ (2016) affects the continuing training participation in $t-1$ (2018).

The control variables (see Appendix (A)) affect all variables. The control variables are measured at t (2019), as size and sector are stable over time, and skill-structure is relatively stable over time.

The analysis is based on the "sem" command in Stata (version 17.1), with maximum likelihood (ML) estimation and bootstrap standard errors, is used. Two models are computed, which only differ in their outcome variables: (1) the participation rate in course-based continuing training and (2) the participation rate in informal continuing training. Both models are presented

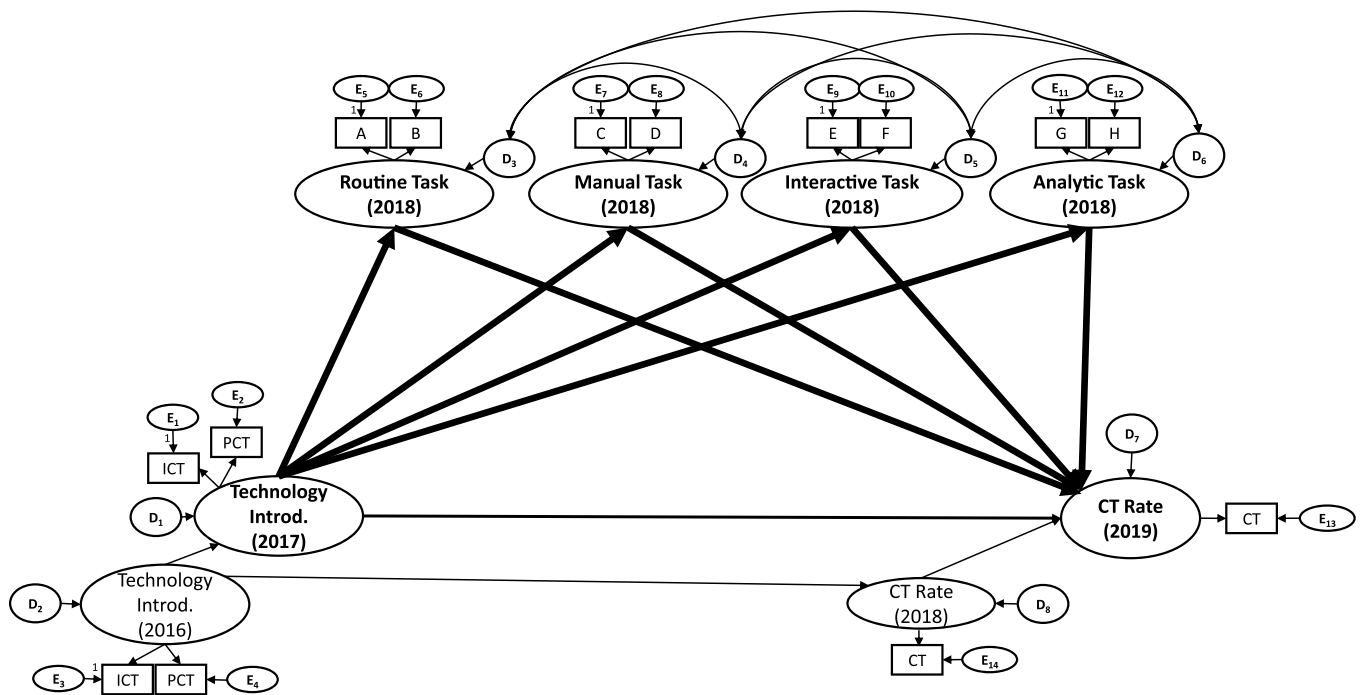


FIGURE 1 | SEM mediation model. *Source:* own representation, read: squared = manifest variables, oval = latent variables (i.e., consists of more than one item or a single item with fixed measurement error (E)), CT Rate = Continuing training participation rate. D = structural disturbance, $\rightarrow$ = causal relations; $\leftrightarrow$ = covariance or correlations; Technology Introd. = Technology introduction.

with and without control variables. In the following, first some descriptive statistics are given, followed by the results of the confirmatory factor analysis (CFA) implemented within the SEM. Finally, the full SEM analyses are presented.

4 | Results

4.1 | Descriptive Results

Table 1 displays the model variables and their correlations with the two types of continuing training. The mean values show that the rates for informal continuing training are higher in firms with technology introduction, supporting **H1**. Contrary to **H2a** and **H2b**, the average frequency of routine and manual tasks is also higher in firms with technology introduction. In accordance with **H2c** and **H2d**, the average frequency of interactive and analytical tasks is higher in firms with technology introduction.

Both dimensions of routine tasks are negatively correlated with course-based continuing training participation (**H3a**), as are both dimensions of manual tasks and course-based continuing training participation (**H3b**). Positive correlations, as predicted by **H3c** and **H3d**, are found for the dimensions of interactive and analytical tasks with participation in continuing training. However, the correlation coefficients—especially for the two dimensions of analytical tasks and participation in course-based continuing training—are very small.

4.2 | Results of the CFA

The detailed results of the final CFA (confirmatory factor analysis; measurement model of the SEM) for (1) continuing

training participation rates in courses and (2) continuing training participation rates in informal continuing training can be found in [Appendix \(B\)](#). In both models, the indicators for the latent variables are correlating significantly with each other.

Both models yield significant results for the Chi²-tests. While such results are undesired, with over 400 observations, the Chi²-test is always significant (Kenny 2024). Therefore, less case-sensitive fit indices are used. For model (1), the RMSEA (root mean square error of approximation) is 0.049, which is below the cut-off point of maximum 0.08 (Awang 2012) and the often-used cut-off point of 0.05. The SRMR (standardised root mean square residual) is 0.029, also below the recommended cut-off point of maximum 0.08 (Byrne 1994; Hu and Bentler 1999) and the stricter cut-off point of 0.05. The CFI (comparative fit index) of model (1) is 0.981, which is above the cut-off point of minimum 0.90 (Byrne 1994) and even above the commonly used cut-off point of 0.95. In sum, the model has a good fit. The fit indices for model (2) are slightly inferior to those of model (1). However, they are all within the limits of the recommended cut-off points.

In comparison to other specifications that measure continuing training directly or use only three dimensions of tasks (i.e., combining interactive and analytical tasks), this model yields better fit indices.

4.3 | Results of the SEMs

Table 2 shows the results for model (1) course-based continuing training without control variables. Including the structural assumptions into the measurement model reduces the CFI and slightly increases the RMSEA and SRMR. Still, the values are in an adequate range. Consequently, the model has a good fit.

TABLE 1 | Model variables (with correlation coefficients; unweighted).

	All				Technology introduction			No technology introduction			Correlation with continuing training	
	Mean/ Prop.	S.D.	Min./ Max.	Obs.	Mean/ Prop.	S.D.	Obs.	Mean/ Prop.	S.D.	Obs.	Course- based	Informal
Technology introduction												
Tech. Intro. 2017	0.37	0.48	0/1	1057	/	/	/	/	/	/	0.0360	0.1406
Tech. Intro. 2016	0.45	0.50	0/1	1057	/	/	/	/	/	/	0.0176	0.1242
Course-based continuing training												
Rate 2019	0.41	0.34	0/1	1057	0.42	0.33	390	0.40	0.34	667	1	0.2849
Rate 2018	0.42	0.34	0/1	1057	/	/	/	/	/	/	0.4760	0.2185
Informal continuing training												
Rate 2019	0.57	0.40	0/1	1057	0.64	0.37	390	0.53	0.41	667	0.2849	1
Provision 2018	0.83	0.37	0/1	1057	/	/	/	/	/	/	0.1451	0.2609
Routine tasks 2018												
Predetermined tasks	0.42	0.22	0/1	1057	0.45	0.22	390	0.41	0.22	667	−0.1025	0.0098
Repetitive tasks	0.44	0.22	0/1	1057	0.46	0.21	390	0.42	0.23	667	−0.1269	−0.0319
Manual tasks 2018												
Using machines/ tools	0.51	0.26	0/1	1057	0.56	0.25	390	0.47	0.27	667	−0.1080	0.0642
Dexterity	0.49	0.23	0/1	1057	0.51	0.23	390	0.47	0.23	667	−0.1362	−0.0103
Interactive tasks 2018												
Informing others	0.56	0.18	0/1	1057	0.58	0.17	390	0.56	0.19	667	0.0426	0.0176
Convincing others	0.54	0.18	0/1	1057	0.55	0.16	390	0.53	0.18	667	0.0277	0.0673
Analytical tasks 2018												
Extending knowledge	0.52	0.17	0/1	1057	0.54	0.16	390	0.51	0.18	667	0.0034	0.0880
Improving/testing	0.48	0.18	0/1	1057	0.52	0.16	390	0.46	0.19	667	0.0070	0.1139
Control variables 2019												
1–19 employees	0.31	0.46	0/1	1057	0.17	0.38	390	0.38	0.49	667	0.0125	−0.1492
20–99 employees	0.32	0.47	0/1	1057	0.28	0.45	390	0.34	0.48	667	0.0091	0.0506
100–199 employees	0.13	0.34	0/1	1057	0.16	0.36	390	0.11	0.32	667	−0.0611	0.0170
200+ Employees	0.24	0.43	0/1	1,057	0.39	0.49	390	0.16	0.36	667	0.0246	0.0917
Primary sector	0.04	0.19	0/1	1057	0.05	0.22	390	0.03	0.17	667	0.0343	0.0133
Manufacturing	0.18	0.38	0/1	1057	0.27	0.44	390	0.12	0.33	667	−0.1312	0.0765
Construction	0.05	0.22	0/1	1057	0.03	0.18	390	0.06	0.24	667	−0.0531	−0.0053
Trade and repair	0.09	0.29	0/1	1057	0.07	0.26	390	0.11	0.31	667	−0.0619	−0.0950
Business services	0.16	0.36	0/1	1057	0.14	0.35	390	0.16	0.37	667	0.0131	−0.0614
Personal services	0.11	0.32	0/1	1057	0.11	0.31	390	0.12	0.32	667	−0.0540	−0.0479
Medical services	0.17	0.38	0/1	1057	0.15	0.36	390	0.18	0.38	667	0.1433	0.1078
Public services and education	0.20	0.40	0/1	1057	0.17	0.38	390	0.22	0.42	667	0.0786	−0.0144
Share low-skilled	0.17	0.23	0/1	1,057	0.17	0.22	390	0.17	0.24	667	−0.2246	−0.0694
Share high-skilled	0.24	0.24	0/1	1057	0.24	0.22	390	0.24	0.25	667	0.1133	−0.0040

Abbreviations: Min. = Minimum value, Max. = Maximum value, Obs. = Observations, Prop. = Proportion, S.D. = Standard Deviation, Tech. Intro. = Technology Introduction.

TABLE 2 | Direct, indirect and total effects of technology introduction and tasks as mediator on course-based continuing training, controlling for previous technology introduction and continuing training rates, based on SEM with ML ($N = 1057$).

	Course-based continuing training		
	Direct effect	Indirect effect	Total effect
Path 1: Relationship between technology introduction and continuing training			
DV: Continuing training participation 2019			
Technology introduction 2017	0.0530 (0.0684)	−0.0575* (0.0276)	−0.0045 (0.0608)
Technology introduction 2016	/	0.0322 (0.0585)	0.0322 (0.0585)
Path 2: Relationship between technology introduction and tasks			
DV: Routine tasks 2018			
Technology introduction 2017	0.1782*** (0.0449)	/	0.1782*** (0.0449)
Technology introduction 2016	/	0.1433*** (0.0396)	0.1433*** (0.0396)
DV: Manual tasks 2018			
Technology introduction 2017	0.3526*** (0.0664)	/	0.3526*** (0.0664)
Technology introduction 2016	/	0.2836*** (0.0623)	0.2836*** (0.0623)
DV: Interactive tasks 2018			
Technology introduction 2017	0.0743** (0.0250)	/	0.0743** (0.0250)
Technology introduction 2016	/	0.0598** (0.0226)	0.0598** (0.0226)
DV: Analytical tasks 2018			
Technology introduction 2017	0.1705*** (0.0385)	/	0.1705*** (0.0385)
Technology introduction 2016	/	0.1372*** (0.0326)	0.1372*** (0.0326)
Path 3: Relationship between tasks and continuing training			
DV: Continuing training participation 2019			
Routine tasks 2018	−0.0638 (0.0683)	/	−0.0638 (0.0683)
Manual tasks 2018	−0.2273* (0.0974)	/	−0.2273* (0.0974)
Interactive tasks 2018	0.1057 (0.1353)	/	0.1057 (0.1353)
Analytical tasks 2018	0.1534 (0.1495)	/	0.1534 (0.1495)
Continuing training 2018	0.6516*** (0.0433)	/	0.6516*** (0.0433)
Path 4 and 5: Impact of previous technology introduction			
DV: Technology introduction 2017			
Technology introduction 2016	0.8043*** (0.1223)	/	0.8043*** (0.1223)
DV: Continuing training 2018			

(Continues)

TABLE 2 | (Continued)

	Course-based continuing training		Total effect
	Direct effect	Indirect effect	
Technology introduction 2016	0.0549 (0.0699)	/ /	0.0549 (0.0699)
Goodness of fit statistics			
Chi ² test model versus saturated (df = 61)	221.981***		
CFI	0.976		
RMSEA	0.050		
SRMR	0.038		

Note: Standardised estimations; bootstrap standard errors with 1000 replications in parentheses (One or more parameters could not be estimated in 139 bootstrap replicates; standard-error estimates include only complete replications). Abbreviations: DV, dependent variable, df, degrees of freedom.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

The results show that technology introduction does not directly affect the course-based continuing training rate. Rather, the technology introduction significantly increases the frequency of all kinds of tasks in firms. A high frequency of manual tasks significantly decreases the participation rate in course-based continuing training. The indirect effect of technology introduction (via the tasks) on continuing training is also significantly negative. This suggests a mediation effect (**H4**), at least through the frequency of manual tasks. With these results, **H1** must be rejected, which is also in favour of the mediation assumption.

With these results, **H2a** and **H2b** must be rejected, as the frequency of routine and manual tasks increase contrary to the hypotheses' assumptions. **H2c** and **H2d** are supported as the frequency of interactive and analytical tasks increases due to technology introduction. **H3b** is supported as well, as the frequency of manual tasks affects the continuing training rates as expected. **H3a**, **H3c** and **H3d** must be rejected—even if the directions of the relationships are as expected—as the results are not significant. Moreover, technology introduction in the year 2016 has an indirect positive effect on the frequency of all tasks.

Table 3 shows the results for model (2) informal continuing training participation. The model's goodness of fit criteria show that the data fit is good as well. In contrast to the model for course-based continuing training, **H1** cannot be rejected, as technology introduction in 2017 directly increases the informal continuing training rates, as well as indirectly through technology introduction in 2016. Similar to the model for course-based training, technology introduction increases the frequencies of all tasks. Therefore, **H2c** and **H2d** can be supported, but **H2a** and **H2b** have to be rejected, just like in the course-based continuing training model. For informal continuing training, the data do not support a direct effect of the frequency of tasks on the informal continuing training rate in 2019, as well as no indirect effect of the technology introduction, **H3a**, **H3b**, **H3c**, **H3d** and **H4** have to be rejected. There is no mediation through tasks for informal training and no relationship between tasks and informal training.

The Appendix (C & D) contains the results for both models with the additional control variables. Again, the goodness of fit statistics for both models indicate a good fit. For (1) course-based continuing training, however, now all hypotheses have to be

rejected. The directions of the associations between the variables remain the same, but become insignificant. For (2) informal continuing training, **H1** still cannot be rejected. Moreover, the technology introduction still significantly increases routine tasks.

In sum, the relationship between technology, tasks and continuing training in a firm depends on the form of continuing training. Technology introduction is directly affecting participation in informal continuing training, while the frequency of (manual) tasks is mediating the relationship between technology introduction and course-based continuing training. Technology introduction is increasing the frequency of all tasks in a firm.

5 | Discussion

The results show that technology introduction had a direct positive effect on the participation rates in informal continuing training, but not on course-based continuing training, providing only partial support for **H1**. This result is partly consistent with previous findings, in which technology indicators are positively related to course-based continuing training (e.g., Baum and Lukowski 2022; Lukowski et al. 2021; Mohr et al. 2016). However, these previous analyses did not consider the mediating role of tasks, or they focused on ICT only, or used entirely different technology indicators. The results of the present article also suggest that technology introduction affects different types of continuing training differently. This result is in line with the work of Lischewski et al. (2020), who found that participation in non-formal and informal training does not depend on the same internal and external factors.

In both SEMs technology introduction had a universal positive effect on the frequency of all tasks. This is against the **H2** hypotheses that predicted heterogeneous effects for the task categories. Only **H2c** for the interactive and **H2d** for the analytical tasks assumed a positive effect of technology introduction, while **H2a** for the routine tasks predicted a negative effect for the technology introduction, and **H2b** for the manual tasks assumed no effect. However, the unexpected increase in routine tasks does not contradict all findings on this topic (e.g., Fernández-Macías et al. 2023; Haslberger 2022). Moreover, results of studies using tasks—even by the same authors—are often not comparable because different definitions, categories,

TABLE 3 | Direct, indirect and total effects of technology introduction and tasks as mediator on informal continuing training, controlling for previous technology introduction and continuing training rates, based on SEM with ML ($N = 1057$).

	Informal continuing training		
	Direct effect	Indirect effect	Total effect
Path 1: Relationship between technology introduction and continuing training			
DV: Continuing training participation 2019			
Technology introduction 2017	0.2622** (0.0855)	−0.0103 (0.0289)	0.2518** (0.0781)
Technology introduction 2016	/	0.3483*** (0.0736)	0.3483*** (0.0736)
Path 2: Relationship between technology introduction and tasks			
DV: Routine tasks 2018			
Technology introduction 2017	0.1724*** (0.0437)	/	0.1724*** (0.0437)
Technology introduction 2016	/	0.1454*** (0.0399)	0.1454*** (0.0399)
DV: Manual tasks 2018			
Technology introduction 2017	0.3497*** (0.0638)	/	0.3497*** (0.0638)
Technology introduction 2016	/	0.2951*** (0.0626)	0.2951*** (0.0626)
DV: Interactive tasks 2018			
Technology introduction 2017	0.0807** (0.0253)	/	0.0807** (0.0253)
Technology introduction 2016	/	0.0681** (0.0244)	0.0681** (0.0244)
DV: Analytical tasks 2018			
Technology introduction 2017	0.1764*** (0.0329)	/	0.1764*** (0.0329)
Technology introduction 2016	/	0.1489*** (0.0350)	0.1489*** (0.0350)
Path 3: Relationship between tasks and continuing training			
DV: Continuing training participation 2019			
Routine tasks 2018	−0.0721 (0.0904)	/	−0.0721 (0.0904)
Manual tasks 2018	−0.1134 (0.1181)	/	−0.1134 (0.1181)
Interactive tasks 2018	−0.0733 (0.1749)	/	−0.0733 (0.1749)
Analytical tasks 2018	0.2703 (0.1181)	/	0.2703 (0.1181)
Continuing training 2018	0.3574*** (0.04937)	/	0.3574*** (0.04937)
Path 4 and 5: Impact of previous technology introduction			
DV: Technology introduction 2017			
Technology introduction 2016	0.8438*** (0.1216)	/	0.8438*** (0.1216)

(Continues)

TABLE 3 | (Continued)

	Informal continuing training		
	Direct effect	Indirect effect	Total effect
Technology introduction 2016	0.3799*** (0.0735)	/	0.3799*** (0.0735)
Goodness of fit statistics			
Chi ² test model versus saturated (df = 61)	223.156***		
CFI	0.975		
RMSEA	0.050		
SRMR	0.039		

Note: Standardised estimations; bootstrap standard errors with 1000 replications in parentheses (One or more parameters could not be estimated in 148 bootstrap replicates; standard-error estimates include only complete replications). Abbreviations: DV, dependent variable, df, degrees of freedom.

** $p < 0.01$; *** $p < 0.001$.

or operationalisations of tasks are used (Biagi and Sebastian 2020). Furthermore, the results cannot show whether the increase is the same for all groups of employees—that is, all employees are affected similarly—or whether it is different for certain employee groups, leading to greater segregation of job tasks and higher inequalities or even to changes in the required skill levels.

The frequency of manual tasks had a negative effect on the course-based continuing training participation, supporting **H3b**. The other three **H3** hypotheses were rejected because the effects were not significant. These results are consistent with findings that employees with more manual tasks participate less in non-formal continuing training (Ehlert 2020; Görlitz and Tamm 2016b; Heß et al. 2019, 2023; Kleinert and Wölfler 2018). From a theoretical viewpoint, this is in congruent with the RBTC hypothesis and the task-based approach. Autor et al. (2003) assume that technological change does not have a huge impact on manual tasks. Consequently, employees with manual tasks might have lower training needs, and employers do not invest in training for employees who have a lot of manual tasks, as training might not be beneficial—even if the frequency of manual tasks is increasing in a firm.

Employees with high-skilled jobs participate more often in continuing training (Offerhaus et al. 2016; Schindler et al. 2011) and have fewer manual tasks (Autor and Handel 2013; Autor et al. 2003; Friedrich 2023; Rohrbach-Schmidt 2019), whereas those with medium- and low-skilled jobs have lower continuing training rates and more manual tasks. Therefore, this strong negative effect of manual tasks on continuing training could increase continuing training inequalities.

For informal training, all **H3** hypotheses had to be rejected, as the effects were not significant. One possible reason might be that participation in informal continuing training is not as dependent on tasks as course-based continuing training, which also fits to the findings of Lischewski et al. (2020) on the differences in informal and non-formal training.

The mediation assumption (**H4**) had to be partially rejected. Only manual tasks were mediating the effect of technology introduction on continuing training in courses, as the direct and total effects were significant. This significant direct effect of manual tasks on continuing training can explain the indirect negative effect of technology introduction on continuing training participation. No significant indirect or total effects were

found for the other tasks. None of the tasks in the informal training model showed significant direct or total effects, and no indirect effect was found.

6 | Contribution, Limitations and Implications

The article examines with SEMs and a unique firm-level data set whether employees' tasks mediate the relationship between technology introduction and continuing training participation in firms. The main aim was to understand the role of tasks in the relationship between technological change and continuing training participation. The article differentiates between (1) participation in course-based and (2) informal continuing training and is one of the first to point out differences in the associations between continuing training, tasks and technology for course-based and informal continuing training in Germany.

The article highlights the importance of including tasks in firm-level research. It contributes to the literature on continuing training that focuses on the relationship between technological change and tasks. By understanding this complex relationship and the crucial role of tasks, the article helps to understand the appearance of continuing training inequalities in times of technological change. Tasks as a mediator could help explain why technology has a different impact on training for different employee groups, that is, no positive effect of technology on training participation for employees in low-skill jobs (e.g., Baum and Lukowski 2022; Wotschack 2020a, 2020b). Identifying patterns between groups is important for addressing inequalities in (access to) continuing training. However, tasks alone do not fully explain continuing training inequalities.

Skill levels are also relevant for participation in continuing training (Blossfeld et al. 2020; Kaufmann and Widany 2013; Offerhaus et al. 2016; Schindler et al. 2011), as they are an important factor for self- and external selection (Blossfeld et al. 2020; Kaufmann and Widany 2013; Offerhaus et al. 2016). Moreover, the content of tasks of employees correlates with their skill level; for example, cognitive tasks are more common among high-skilled employees (e.g., Autor and Handel 2013; Autor et al. 2003; Friedrich 2023; Rohrbach-Schmidt 2019). The models presented do not differentiate for individual differences within and between individuals. The relationships between technology, tasks and training may differ depending on the skill group.

Further limitations are that the sample might be biased due to the high panel attrition. Therefore, the results might not be generalisable to all firms in Germany. In addition, the measurement of informal training is imprecise. It is not possible to differentiate between the different types of informal training or the devices used for it.

The measurement of technology introduction is also very rough, as it covers only two big categories (ICT and PCT), without a special focus on computerisation and digitalisation. However, in both categories, new technology is oftentimes computerised or digitalised. Still, within and between those categories, varying impacts on tasks and training are possible. It cannot be ruled out that the newly introduced technology is not digital or not computer-controlled. Moreover, the timeframe for the technology introduction just refers to the last year. Some technology introductions can take longer, as the process, from buying the technology to all employees properly using the technology, can span over years. Also, it accounts for the introduction of technology in the previous year only. There might be an impact of even earlier technology introductions. Additionally, the rise of artificial intelligence (AI) is changing the working world in a way that is different from previous technological change, as different tasks may now be replaceable (Acemoglu and Restrepo 2019).

These limitations provide a starting point for further research. In particular, research should focus on the lack of differentiation between employees' skill levels. The effects of technology and tasks may differ for employees with different skill levels. Furthermore, research should examine the impact of AI on ongoing training inequalities and the relationship between technology, tasks and training.

Although Germany has a highly regulated and strong dual apprenticeship system, continuing training in Germany is less state-regulated and strongly dependent on firms (Allaart et al. 2009; Roosmaa et al. 2019). As such, Germany represents a special institutional context for continuing training, and the results may not be generalisable to all countries. However, even when differences in the changes in tasks arise, technological and task changes are a global trend (Biagi and Sebastian 2020; Hardy et al. 2018), and continuing training serves as a universal adaption strategy. Therefore, the key insights of this analysis may still hold relevance for other national contexts.

In the European political and academic discourse, continuing training is seen as a key means of ensuring the employability of employees in times of technological change. Moreover, continuing training could reduce educational inequalities and contribute to social inclusion (Offerhaus et al. 2016). However, in reality, continuing training participation is highly unequally distributed (Blossfeld et al. 2020; Offerhaus et al. 2016; Schindler et al. 2011). The results presented emphasise that changes in technology indeed affect participation in course-based and especially informal continuing training, but also highlight the strong influence of job tasks on continuing training. Technology introduction and employees' tasks—which are unequally distributed—are joint predictors of continuing training participation in firms, and with that, whether employees can adapt to the changing work environment or not.

Tasks as a mediator between technology and participation in course-based continuing training possibly reinforce continuing training inequalities in times of technological change. This

reinforcement of inequalities is problematic, especially as those employees with low-skilled jobs, who more likely to perform manual tasks, are also those who are already less likely to participate in continuing training. Moreover, an increase in manual tasks within a firm could lead to a decrease in the overall need for continuing training, which could further widen the continuing training gap as investment in continuing training could shift towards those without manual tasks, that is, those in high-skilled jobs (cf. Muehlemann (2025), in relation to AI). This is potentially dangerous. Employees performing manual tasks are at risk of being left behind or replaced if they cannot adapt to technological change that affects their work environment, directly or indirectly.

The results highlight the important role of tasks next to skill levels for developing policies that address persistent continuing training inequalities. For example, implementing programmes and incentives for firms that promote participation in continuing training depending also on tasks rather than solely on skill-levels. Moreover, since participation in informal training is less dependent on tasks and is more directly influenced by technological change, policy developments should focus on creating spaces and time for informal training, as well as better recognition for the skills acquired through it.

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Conflicts of Interest

The author declares no conflicts of interest.

Data Availability Statement

I use data from the BIBB Establishment Panel on Training and Competence Development long dataset from 2011 to 2021 (10.7803/371.1121.1.2.10) (Friedrich et al. 2023). The survey was conducted by the Federal Institute for Vocational Education and Training (BIBB). Data access can be granted via Remote Data Access and One-Site Use from the BIBB Research Data Centre.

Endnotes

¹Recent approaches define human capital more broadly and implement modifications and critiques (c.f. new training literature [Bellmann and Leber 2019]).

²'Using tools or operating machines (A)'; 'Using specific manual skills and finger dexterity (B)'

³'Tasks are predetermined in each detail (C)'; 'Tasks are repetitive in each detail (D)'

⁴'Informing customers and patients (E)'; 'Convincing others and mediating compromises (F)'

⁵'Completing and extending expert knowledge continually (G)'; 'Improving existing or testing new procedures (H)'

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Appendix