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ORIGINAL ARTICLE

The link between computer use and job satisfaction: The mediating role of job tasks and task discretion

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Abstract
This study focuses on the consequences of the use of computerized work equipment (hereafter: computer use) on the content and quality of work. It investigates, first, the relationship between computer use and both job tasks and task discretion and, second, their mediating role for the relationship between computer use and job satisfaction. With our German-UK comparison, we contribute to the long-standing debate on the upskilling/de-skilling nature of the use of technology and its repercussions on the quality of work. We analyse data from the Skills and Employment Surveys for the UK and the BIBB/BAuA Employment Surveys for Germany using structural equation modelling. In line with the literature on routine-biased technological change, we show that computers are complementary to the performance of less routine and more abstract cognitive tasks and that this relationship is conducive to a higher level

of task discretion and job satisfaction in both countries. Accounting for differences in job tasks performed, we find a negative direct effect of computer use on both task discretion and job satisfaction in the United Kingdom but not in Germany. Our results indicate that the ultimate effect of computer use on both task discretion and job satisfaction depends on the institutional contexts in which technology is introduced.

1 | INTRODUCTION

Since their early appearance in the workplace, computers have spurred a vivid debate on their consequences for work, organizational and social processes. At the core of this debate lies the question of whether adopting technology leads to an upgrading of skills or a downgrading of work (Attewell, 1987; Bailey & Leonardi, 2015; Bloomfield & Coombs, 1992; Gallie, 1991). With the digital transformation of work, this question has recently regained importance, partly because the skill requirements of jobs are strongly associated with job quality and ultimately with workers' job satisfaction (Gallie, 2007) as well as with labour market inequalities (e.g. in terms of earnings) (Autor, 2022; Kristal & Edler, 2019).

Despite its relevance, answers to the question of the upskilling or de-skilling nature of technology—and the related consequences of technology for job quality—remain controversial. Scholars from a largely Marxist tradition argue that technology is an instrument used to standardize labour processes by reorganizing work into a series of low-skilled tasks and that technology has therefore resulted in lower-skilled jobs with little intellectual content and autonomy (Braverman, 1974; Jenkins & Sherman, 1979). Various qualitative case studies support this perspective empirically (e.g. McNally, 2010). In contrast, scholars who support the upskilling thesis suggest that a technology-driven decentralization of information (Acemoglu et al., 2007) and the complementarity of technology to non-routine cognitive tasks have increased the demand for skills and led to large human-capital endowments (Autor et al., 2003; Goldin & Katz, 1998). This upskilling perspective is supported by a series of quantitative studies that document a steady growth in abstract tasks and skilled occupations, with corresponding benefits for wages (e.g. Breemersch et al., 2017; Fonseca et al., 2018; Keister & Lewandowski, 2017).

These conflicting perspectives and findings might result from conceptual differences in the definition of skills: While upskilling proponents typically focus on the type and range of tasks performed, de-skilling proponents refer to the degree of autonomy and to workers' control over the labour process. Several authors therefore suggest considering both *distinct yet related* dimensions of occupational skills to derive a better understanding of the relationship (a) between technology and both upskilling and de-skilling and (b) between technology and the quality of work (e.g. Felstead et al., 2007; Martinaitis et al., 2021; Rolfe, 1986, 1990; Spenner, 1983, 1990; Vallas & Beck, 1996). This conceptual differentiation is also supported by the fact that trends in job tasks and task discretion do not necessarily evolve in the same direction (Gallie, 2012). Moreover, whether technology and the quality of work are positively or negatively related might depend on the type of job tasks and on workers' task discretion (e.g. Hardin, 1960; Parayitam et al., 2010; Shepard, 1977).

Our study therefore addresses two research questions: First, we examine the link between computer use (i.e. the use of any computerized equipment at work) and both job tasks and task discretion and thereby reveal whether upskilling and de-skilling are indeed mutually exclusive. Second, we investigate the mediating role of both job tasks and task discretion in the relationship between computer use and job satisfaction. We take computer use as an indicator of the application of technology because computers are the most widespread form of technology used among the labour force (Autor et al., 2003; Elsayed et al., 2017; Green, 2012; Menon et al., 2019; Spitz-Oener, 2006).

In this aricle, we consider skills as a multi-dimensional feature of jobs rather than an individual characteristic of workers. This means that we do not refer to skills possessed by individuals but rather to skills used at the workplace (in other words, the sets of occupational and organizational skill requirements). This workplace/organizational understanding of skills is of primary interest for our study because production technologies are adopted at the organizational level and, therefore, they primarily alter the occupational and organizational demand for skills and not necessarily the different types of skills individuals possess.

We compare these relationships in Germany and the United Kingdom as two exemplary cases of different types of production regimes. This comparison challenges the deterministic notion of the upskilling and the de-skilling thesis because both argue that the impact of technology is common to all institutional and organizational contexts (e.g. Bailey & Leonardi, 2015). We maintain that while computers are generally complementary to a specific set of tasks and substitutive to the performance of others, their impact on organizational practices—and thus the extent to which they impact the degree of workers' task discretion—is contingent on the specific institutional arrangements in which they are used (Autor et al., 2002). Germany and the United Kingdom are characterized by clearly different institutional arrangements regarding their market coordination (Estevez-Abe et al., 2001; Hall & Soskice, 2001), skill formation (Thelen, 2004) and corporate governance (Waddington, 2004). The mixture of industrial and managerial practices and cultures in these two countries might therefore influence how computers are adapted to production processes and thereby shape workers' task discretion and job tasks as well as their overall job satisfaction (Gallie, 2007, 2011; Green & McIntosh, 2001).

Contributing to the existing literature, our study theoretically and empirically highlights how job tasks and task discretion are related yet distinct aspects of occupational skills and investigates their role as mediators in the relationship between technological innovation and workers' job satisfaction (i.e. workers' assessments of the quality of work). Moreover, results from our study are consistent with the idea that national institutional contexts moderate the impact of technology on work organization and job satisfaction.

2 | A BRIEF SYNOPSIS OF THE UPSKILLING/DE-SKILLING DEBATE

In the European debate, Friedmann (1946) is one of the most influential authors to argue that the use of technology can lead to a decline in the quality of work by negating workers' *craftsman-like* skills/tasks and removing workers' capacity to control the production process. As Gallie (2012) notes, Friedmann identifies technology as the main factor behind the *Taylorization* of work tasks and thereby behind the elimination of the opportunity for workers to exercise discretion, autonomy and control over their jobs. In the US debate, Leavitt and Whisler (1958) were among the first to claim that computer and information technology (ICT) lead to a centralization of decision making, authority and power in the hands of a 'tight little oligarchy' of high-ranking managers and employers. Similarly, Braverman (1974) argues that the automation of the labour process is a means of transferring control, discretion and autonomy from the shop floor to management because automation supports the application of scientific management and thus also management's ability to ensure that labour power is successfully converted into labour.

The underlying idea of the de-skilling thesis is that information is a source of power and that workers and middle management would therefore lose power if information gathered in computerized systems becomes accessible to top management. Supportive empirical evidence has been provided by a large body of organizational studies (e.g. George & King, 1991). The *equation between required skills and task discretion* is crucial to the de-skilling perspective, with discretion understood as workers' ability to choose between alternative courses of action and to exercise control over the way, order and turnaround times in which tasks are performed. Reducing skills thus entails a fragmentation of tasks, closer supervisory control and a loss of workers' autonomy and discretion in the workplace (Blauner, 1964; Fox, 1974; Gallie et al., 2003; Jaques, 1956, 1967; Spenner, 1983, 1990).

In contrast, proponents of the upskilling thesis argue against any inherently centralizing tendency of computer technology (Lindbeck & Snower, 2000; Radner, 1993; Wyner & Malone, 1996). They stress that such a tendency could lead to substantial costs for management and that computers may instead promote the organizational decentralization of power and control due to shared information or several management levels. An upskilling scenario is echoed in the literature on *skill-biased technological change* (SBTC), which suggests that computer technology, education and skills are strongly complementary and that technology thus favours higher returns for skilled workers and increases the demand for skills (Goldin & Katz, 1998). This position is strengthened by numerous empirical studies that document strong relationships between ICT use, high-skilled tasks, the demand for tertiary-educated workers and rising college wage premiums (e.g. Bresnahan et al., 2002; Goldin & Katz, 2008).

Due to the empirical evidence of polarizing trends in both earnings and occupational structures (Acemoglu, 1999), the SBTC thesis was developed into the thesis of *routine-biased technological change* (RBTC) (Acemoglu & Autor, 2011; Autor et al., 2003; Goos et al., 2009), whose key argument is that computer technology modifies the job tasks required and performed in the workplace, which are classified along two distinct dimensions: *routine* versus *non-routine* and (analytical and interpersonal) *cognitive* versus *manual* tasks.

While SBTC relates the introduction of computers to a wider upskilling and related changes in earnings structures mainly through the complementarity of computers to skill levels and through returns to higher-educated workers, it makes no *direct* claim regarding the relationship between technology and the content of work in terms of job tasks or task discretion. In contrast, RBTC connects technology and the evolution of earnings and occupational structures through its relationship to the types of tasks performed by workers in different occupations and thus also makes an argument for the relationship between computers and job tasks. According to RBTC, technology serves as a substitute for explicit and codifiable routine-task operations[1]—at both the low and middle level of the occupational hierarchy—and as a complement to higher-level cognitive tasks, resulting in a steady growth of skilled jobs. However, the RBTC literature also signals a parallel increase in non-automatable manual tasks, thereby causing a U-shaped polarization between high-skilled positions and low-skilled jobs (Acemoglu & Autor, 2011; Autor et al., 2003; Goos et al., 2009).[2]

While research has generally agreed on the complementarity between computers and more abstract tasks, there is much less agreement for its implications regarding occupational structures. Socioeconomic research has found mixed evidence and there is lack of agreement regarding a common process of polarization across equally developed countries. Instead, research has highlighted cross-national differences in processes of occupational change, stressing the importance of national institutional arrangements (Fernández-Macías, 2012; Haslberger, 2021; Oesch & Piccitto, 2019; Oesch & Rodríguez Menés, 2011; Salvatori & Manfredi, 2019).

The de-skilling and upskilling perspectives usually refer to two different dimensions of occupational skills: the upskilling perspective points to the complexity and variability of job *tasks*, while the de-skilling argument refers to task *discretion*.

The argument that task discretion and the complexity of tasks are two fundamental yet distinct dimensions of skills follows from the work of Fox (1974), Friedmann (1961) and Spenner (1983, 1990). For example, Spenner (1990, pp. 402, 403) differentiates between *substantive complexity* ('the level, scope and integration of mental, manipulative and interpersonal tasks in a job') and *autonomy control* ('discretion or leeway available in a job to control the content, manner and speed with which tasks are done'). Similarly, Rolfe (1986, 1990) distinguishes between *technical complexity* and *discretion* based on the same idea: while job tasks are carried out as organizational requirements, the nature of such requirements does not dictate how tasks should be completed, this being determined by the hierarchy of power within an organization (see also Autor et al., 2002; Martinaitis et al., 2021; Myles, 1990). Both Spenner's and Rolfe's complexity dimensions are closely related to what more recent literature on RBTC defines as *job tasks* (Autor, 2015; Autor et al., 2003; Goos et al., 2014). We therefore use the term job tasks to refer to this first dimension of skills and task discretion to label their second dimension.

Although most evidence for de-skilling has focused on task discretion, this does not mean that proponents of the de-skilling perspective do not engage with the issue of task complexity. In fact, in his original work, Braverman (1974) suggested that the decline in discretion and autonomy results from the reduction of workers' technical capacity and the fragmentation of job tasks. From this perspective, the main difference between these two approaches lies on their expectations of how, and why, technology impacts on tasks complexity. In this respect, de-skilling proponents more often focus on discretion and control over the work process as the most salient dimension affected by technology, while upskilling proponents mainly refer to task complexity (and pay little attention to its potential interplay with task discretion), eventually reaching conflicting conclusions.

A clear distinction between these two dimensions of skills may allow to partially reconcile the two perspectives without necessarily implying a unidimensional up- versus de-skilling view of technological change. This distinction is particularly relevant in the case of digital technologies, which have been repeatedly observed to complement more complex and abstract tasks, while at the same time enabling detailed monitoring of workers' procedures. This view has received empirical support (e.g. Iacono & Kling, 1991; Vallas, 1993; Vallas & Beck, 1996): For example, Zuboff (1988) identified a general upskilling of production work for more abstract job tasks but a minimal expansion of autonomy.

Much of the literature reviewed here intrinsically values job skills to the extent to which they improve working conditions and workers' well-being. The upskilling–de-skilling debate eventually revolved around the effect of technologies on the quality of work. Both upskilling and de-skilling perspectives suggest that technology might influence work quality through its association with skill requirements, that is, increasing it by augmenting cognitive and abstract tasks and/or decreasing it by reducing control over production processes. Indeed, the positive association of occupational task content and task discretion with job satisfaction is well established (Hackman & Oldham, 1976; Humphrey et al., 2007).

Besides such an indirect impact of technology on job quality and workers' satisfaction—our main research questions—technology may also have a direct impact on workers' satisfaction. To take one example, recent research has shown that technology may have a direct negative influence on workers' well-being, an association usually referred to as 'technostress' (Brod, 1984). This research has identified several ways through which digital technologies can worsen the work experience beyond its association with skill use and discretion, for example, an increased feeling of work overload (e.g. because working with technologies increases the pace of work, the frequencies of interruptions, working hours and expectations for reaction times in communication), an increased feeling of uncertainty (caused by the constant change in work requirements and associated fear of job loss or degradation), the blurring of work and other life domains (resulting in work-life conflicts and worse recovery from work), concerns induced by technical breakdowns, errors and low usability, or simply technology anxiety (Dragano & Lunau, 2020; Tarafdar et al., 2007).

This brief synopsis of the upskilling/de-skilling debate highlights the relevance of disentangling different dimensions of occupational skill requirements in order to understand the skill-biased nature of technological innovation and its ultimate impact on job satisfaction. However, while studies have shown that job tasks and task discretion may be affected differently by technology, how the interplay between these two dimensions determines the overall effect of technology on job satisfaction remains poorly understood. Moreover, researchers in this area—using mostly single-country cases—are quick to generalize their findings and might thereby underestimate the role of the institutional context for the implementation of technology. With our comparative study, we contribute to a more-comprehensive understanding of the relationship between the implementation of technology (i.e. the association between computer use in the workplace, job task, and task discretion) and job satisfaction in different political economic arrangements.

3 | EMBEDDEDNESS IN INSTITUTIONAL CONTEXTS

Both the upskilling and de-skilling perspectives are based on a deterministic understanding of technological change and therefore assume that technology similarly impacts job tasks and task discretion across countries (with similar levels of economic development). However, cross-country studies reveal that workers in similar occupations can be exposed to different job tasks and to very different styles of managerial supervision and control (De La Rica et al., 2020; Gallie, 2007, 2011; Holman & Rafferty, 2018; Lincoln & Kalleberg, 1990; Maurice et al., 1986).

Such country differences could result from the fact that capitalist economies follow different production strategies, which favour different types of employment relationships, industrial relations practices, skill-formation regimes and skills equilibria (tasks and discretion) (Estevez-Abe et al., 2001; Gallie, 2007, 2011; Hall & Soskice, 2001). In this respect, approaches related to *production regimes theories* (Gallie, 2007; Hall & Soskice, 2001) are highly relevant for differences between countries as they provide an account of institutional configurations affecting work experience at the 'meso' level (i.e. because of differences in relations between owners and managers, subcontracting relations, product and innovation strategies, industrial relations) as well as at the 'micro' level (e.g. in terms of skills acquisition, the degree of job control, participation at work, job security and the quality of employment). Thus, countries' institutional characteristics affect the work experience, which in turn impacts on job satisfaction, workers' motivation and psychological well-being (Soskice, 1999; Gallie, 2007).

Moreover, the production regimes approach is particularly relevant in understanding country differences in technology implementation since it focuses on institutionally generated differences in managerial preferences regarding skill demands and job organization. For example, the above-mentioned theories concerning upskilling and de-skilling suggest that the skill restructuring associated with the implementation of technical tools is primarily an employer's prerogative; similarly, an organizational understanding of skill requirements suggests that the degree of task discretion and task complexity are primarily an organizational requirement designed by management. Given that the production regime perspective stresses various economic and institutional incentives driving organizational and employment strategies, it is a fruitful theoretical approach to investigate cross-national differences in the relationship between technology and work content.

Briefly, the two ideal-typical models of political-economic arrangements identified by production regimes theories are coordinated Market Economies (CMEs) and Liberal Market Economies (LMEs). CMEs—exemplified by Germany—are characterized by a set of institutions (e.g. centralized and coordinated wage bargaining, the presence of work councils and strong vocational education and training systems) that incentivize firms to adopt employment strategies that rely on highly skilled labour endowed with extensive work autonomy, responsibilities and the encouragement to share information (Estevez-Abe et al., 2001; Herrigel & Sabel, 1999). In contrast, firms in LMEs—exemplified by the United Kingdom and the United States—rely heavily on competitive market relationships and hierarchies to organize relationships between workers and other actors. Top managers typically have strong, unilateral control over both the firm and production processes, including substantial freedom to hire and fire in order to adapt to fast-changing employment conditions and product markets. Due to highly fluid labour markets, firms adopt employment strategies based on a workforce that is mainly endowed with general skills and low(er) company attachment.

The underlying idea is that these different national institutional contexts are associated with different managerial strategies and practices of organizing work at the firm level because firms have a comparative advantage if they behave according to the respective institutional rationale (Hall & Soskice, 2001; Holm et al., 2010; Lopes et al., 2017). The implementation of new technologies and the consequences of these technologies for job tasks and task discretion are hence likely to differ in these two institutional arrangements. In CMEs, in which workers' occupation- and industry-specific skills more strongly contribute to the organization of product lines and production processes, firms should (1) use technology more often to relieve their (comparatively well-paid and well-trained) workers from simple routine tasks and (2) increase the use of workers' analytical and problem-solving potential. However, due to the prevalence of diversified quality production in Germany (Sorge & Streeck, 2016) and the more-consensus-based approach to decision making in CMEs (Edlund & Grönlund, 2008), technology-implementation processes are influenced by strong trade unions and high levels of employment protection, especially in manual-intensive industries (see also Baccaro et al., 2018). Routine tasks might thus be more integrated than substituted when implementing computerized work tools. Here, routine tasks also more often include tasks that require manual dexterity and occupation-specific skills than in LMEs, which are more often associated with simple tasks. In LMEs, in which firms have less access to a highly trained workforce and face higher labour turnovers, technology can be used as an instrument to more effectively increase control over work processes, to increasingly standardize tasks and to reduce skill requirements (Dobbin & Boychuk, 1999).

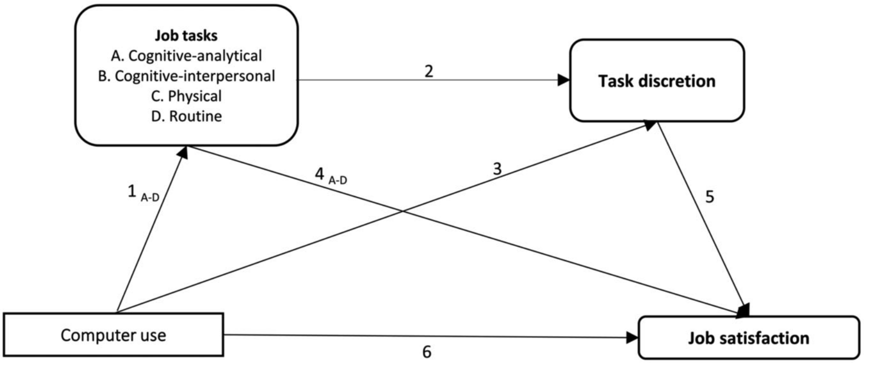

FIGURE 1 Stylized theoretical model of the role of tasks and task discretion on the relationship between computer use and job satisfaction.

Comparative case studies show very high variability in the degree of discretion that workers exert on their job—regardless of similar technological work settings—according to diverse forms of managerial control and skill regimes (Gallie, 2007; Lincoln & Kalleberg, 1990). Research has shown that workers and their representatives have a higher degree of involvement in designing their work and determining the terms of their employment in Germany (as a CME) compared to LMEs (Doellgast et al., 2009; Frege & Godard, 2014; Zoghi & Mohr, 2011). For instance, Shire et al. (2002) and Doellgast (2008, 2010) observed that call centres in Germany designed jobs more broadly and monitored employees less intensively compared to similar organizations in the United Kingdom and the United States. Similarly, Finegold et al. (2000) found that German hotels were characterized by higher levels of job rotation and lower employee turnover than those in the United Kingdom and the United States. Dobbin and Boychuk (1999) report strong differences in workers' task discretion between Scandinavian (social-democratic) countries and LMEs and conclude that production regimes and managerial systems may favour skill- versus rule-governed modes of production, with contrasting consequences for job autonomy. Hence, to gain a better understanding of how production and work are restructured in response to technological innovations, the institutional context in which firms operate must be considered.

Due to the different types of institutional embeddedness of managerial strategies in Germany and the United Kingdom, it might be as misleading to assume a common trend towards de-skilling in terms of a generalized loss of workers' discretion as it would be to expect a common upskilling trend towards an increase in non-routine or cognitive tasks.

Before presenting our comparative expectations, we next discuss our theoretical model of the mediating role that job tasks and task discretion play in the relationship between computer use and job satisfaction.

4 | THEORETICAL MODEL AND EXPECTATIONS

Figure 1 presents our stylized theoretical model. The relationship between computer use and both job tasks and task discretion as two distinct yet related dimensions of skills (our first research question) is indicated by Paths 1 and 3, respectively. The mediating role of the two skills dimensions for the relationship between computer use and job satisfaction (our second research question) is indicated by the joint Paths 1–4 and 3–5, respectively. Path 6, which is not subject of our study, indicates the remaining direct influence of computer use at work on job satisfaction, independent of (i.e. after controlling for) job tasks and task discretion. One possible explanation is that the use of computerized equipment in the workplace can have a direct *alienating* effect due to technostress or computer anxiety (e.g. Ayyagari et al., 2011; Brod, 1984; Ragu-Nathan et al., 2008).

We begin with the two mediations and derive expectations about country differences. We then present some considerations on variations across groups of workers, focusing on occupational class position and participation in job-related training.

Research has consistently shown that the diversity and complexity of job tasks (Path 4) as well as the possibility of controlling the pace, timing and methods of work (Path 5) are associated with higher levels of job satisfaction (Hackman & Oldham, 1976; Humphrey et al., 2007). Concerning the proposed mediation via job tasks (Paths 1–4), RBTC research argues that computers complement (analytical and interpersonal) cognitive tasks yet substitute (manual and non-manual) routine tasks. Thus, we expect that computer use should complement non-routine (cognitive and interpersonal) job tasks and reduce routine tasks (Path 1), which should thus positively influence workers' job satisfaction (Path 4) (see also Taber & Alliger, 1995).

Through their complementarity to more non-routine (especially cognitive-analytical) tasks, computer technologies may eventually be conducive to higher levels of task discretion (Paths 1–2), because non-routine tasks are more difficult for employers and management to monitor, which may thus also yield higher job satisfaction (Path 5) (Nassab, 2008). Gallie et al. (2003, p. 419) interpret the rise in task complexity as being 'accompanied by rising task discretion,' whereas Green (2012) proposes that discretion impacts job tasks. While the lack of appropriate longitudinal data on work practices impedes the possibility to empirically study the opposite directions of this relationship, in order to properly model the direct effect of computer use on task discretion (i.e. net of differences in tasks between computer users and non-users), we follow Gallie et al. (2003) and Green et al. (2022) and impose a direct relationship between job tasks and task discretion, as indicated by Path 2. This choice is also consistent with a long strand of literature on social stratification and mobility which suggests that workers' position in the class structure is the result of their degree of independence and autonomy, which in turn is a function of the complexity and monitorability of their work (Breen, 2001; Erikson & Goldthorpe, 1992).

While the use of computerized equipment is complementary to more abstract and less monitorable tasks, it may simultaneously (according to the de-skilling perspective) increase the possibility for management to monitor and control work by centralizing information, independent of the type of job tasks (Path 3). This direct impact on task discretion could be another channel via which computer use generates differences in job satisfaction (Paths 3–5). This association between task discretion and job satisfaction is well established (Hackman & Oldham, 1976; Humphrey et al., 2007).

Existing literature has shown the technical complementarity between computers and job tasks. Thus, one might assume a similar relationship with the type of tasks performed in the two countries. However, after accounting for computers complementarity to the type of tasks performed, we should expect different associations between computer use, workers' task discretion and job satisfaction because of the differences in managerial strategies in Germany and the United Kingdom (as discussed above). In the United Kingdom, where institutional arrangements tend to favour the adoption of centralized and non-coordinated production strategies, less worker participation and higher levels of managerial control, we expect the direct relationship between computer use, discretion and satisfaction to be more consistent with a de-skilling perspective. That is, computer use should reduce workers' discretion over their task performance and satisfaction with their job content. In contrast, because of Germany's coordinated production strategies, computer use should increase or support the discretionary effort of employees and the satisfaction with the content of their job.

Furthermore, the mediating role of job tasks and task discretion in the interplay between computer use and job satisfaction might differ not only across institutional contexts but also across groups of workers (within countries). We consider two worker characteristics to be closely related to this interplay: *occupational class position* and *further training*. Both social stratification and labour market research highlight the importance of the monitoring problem for justifying the favourable position of upper-service-class positions (Erikson & Goldthorpe, 1992). Hence, employees in service-class positions (i.e. the salariat) might experience computer use differently than other workers because computers are considered to be largely *complementary* to the non-routine cognitive tasks typical of higher-level occupations and to simultaneously constitute a powerful instrument for controlling and monitoring the discretionary efforts of high-educated workers, whose activities are intrinsically difficult to monitor. For other workers, computer use might be less influential for task discretion because their work is characterized by a higher degree of routine (cognitive or manual) tasks, which are generally easier to monitor. Occupational class could thus be a moderator for the two mediations. We therefore expect that job tasks mediation should more positively influence job satisfaction among the salariat than among other classes, whereas mediation via task discretion should more negatively affect their job satisfaction because the salariat risk losing more autonomy.

Participation in job-related adult training might be another relevant moderator related to the mediating role of job tasks. Adult training might increase workers' proficiency in ICT skills, which could contribute to increasing requirements in problem-solving or other cognitive job tasks (Path 4) (Cedefop, 2015; Desjardins & Rubenson, 2013). Accordingly, we expect to find a (stronger) direct negative effect of computer use on job satisfaction for non-trained workers and a more-positive mediating effect of jobs tasks for trained workers.

Due to the difficulty of deriving concrete expectations about country differences for these two potential moderators, we include the two moderation analyses as an explorative analytical step in our study. We also include educational attainment as a control variable in the analyses (not shown in Figure 1) and allow education to co-vary with all variables since it arguably influences computer use and all other investigated jobs aspects.

5 | RESEARCH DESIGN

5.1 | Data and variables

We use individual-level data from the BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany and the Skills and Employment Survey (2006, 2012, 2017) for the United Kingdom. Both surveys provide comparable and high-quality information on our variables of interest (see below). We restrict our sample to employees aged 20–65. After dropping cases with missing information on at least one variable of interest, our final sample consists of 49,446 cases for Germany that range from 16,040 to 16,778 cases per survey year. For the United Kingdom, sample sizes are considerably smaller, with 11,281 cases in total and 2,740–5,853 cases per survey year.[3]

Data were collected using the *job requirements approach*, which is essentially an adaptation of occupational psychologists' methods in the context of socioeconomic surveys. This approach provides information on several job-related characteristics, such as the use of computerized work equipment, job tasks, task discretion and job satisfaction. Table 1 reports information on each

TABLE 1 List of items on latent constructs of interest

The United Kingdom	Germany
Job satisfaction	
Satisfaction with the opportunity to use your abilities[a]	Satisfaction with opportunities for applying skills[b]
Satisfaction with able to use your own initiative[a]	Satisfaction with type and content of work[b]
Satisfaction with this aspect of own job—the work itself[a]	Satisfaction with work on the whole[b]
Job tasks	
Cognitive-analytical	
Importance of spotting problems or faults[c]	Confronted with new tasks[d]
Importance of working out causes of problems/faults[c]	Recognize and close your own gaps in knowledge[e]
Importance of thinking of solutions to problems[c]	Improve existing procedures or try something new[d]
	React to problems and solve them[e]
Cognitive-interpersonal	
Importance of counselling, advising or caring for customers or clients[c]	Purchasing, procuring, selling[e]
Importance of dealing with people[c]	Advertising, Marketing, Public Relations, PR[e]
importance of selling a product or service[c]	
Physical	
Importance of physical stamina[c]	Work standing up[d]
Importance of physical strength[c]	Lift and carry heavy load[d]
Routine	
How much variety in job[h]	One and the same operation is repeated in every detail[e]
How often work involves short repetitive tasks[f]	Execution of work is prescribed in every detail[e]
Task discretion	
Influence personally have on: how hard work[g]	Influence the amount of work assigned to you[e]
Influence personally have on: how to do the task[g]	Plan and schedule your own work yourself[e]
Influence personally have on: what tasks to do[g]	
How much choice over the way in which job is done[g]	Decide for yourself when to take a break[e]

Original scales:
[a] 1 (*completely satisfied*) to 7 (*completely dissatisfied*);
[b] 1 (*not satisfied*) to 4 (*very satisfied*);
[c] 1 (*essential*) to 5 (*not at all*);
[d] 1 (*never*) to 4 (*frequently*);
[e] 1 (*never*) to 3 (*frequently*);
[f] 1 (*never*) to 5 (*always*);
[g] 1 (*A great deal*) to 4 (*none at all*);
[h] 1 (*a great deal*) to 5 (*none at all*). Some variables are reverse coded to facilitate interpretation.

selected item and its latent construct of reference.

More in detail, our variable *computer use* measures the use of any computerized equipment at work. This broad indicator is also useful in accounting for workers for whom computer use may not be a central component of the job but is relevant in shaping workplace dynamics. In the United Kingdom, computer users include workers who reported that computer use is *essential*, *very important* or *fairly important* in their job, whereas non-users are those who reported *not very important* or *not important at all*. In Germany, computer users are defined as workers who reported that they work with computers *frequently*, whereas non-users are those who do so only *sometimes* or *never*. Different specifications of the variable yield similar results. The broad indicator of usage (rather than complexity) of computerized equipment aims at capturing the impact of workplace technology on job tasks and workers' autonomy, regardless of the level of complexity or type of activity. Computerized work technologies can be valuable instruments for the restructuring and monitoring of jobs, regardless of the level of complexity required or their specific application. In contrast, the level of complexity of computer use itself defines job tasks already.

We operationalize workers' *job satisfaction* with an indicator consisting of three items about workers' satisfaction with both the skills content of their job (in terms of job tasks and task discretion) and their job altogether. Although the wording of these items differs slightly across the two country datasets, we consider them as clearly belonging to the same latent construct of interest. Cronbach's alphas of 0.76 for Germany and 0.84 for the United Kingdom indicate reasonable levels of reliability. Table 2 shows average levels of normalized items of job satisfaction for computer users and non-users: In Germany and the United Kingdom, computer users are more likely than non-users to be satisfied with each of the three satisfaction dimensions.

To measure *job tasks* and *task discretion*, we identified a set of items from each dataset that is comparable and clearly belongs to only one of the latent constructs of interest. Conceptually, we follow Autor et al. (2003) and empirically integrate adaptions by Green (2012) and Spitz-Oener (2006). Using factor analysis (FA), we obtained four factors that capture different task domains—cognitive-analytical, cognitive-interpersonal, physical and (manual and non-manual) routine—and one indicator that captures task discretion, thereby confirming the theoretical definition of the latent skills dimensions for both countries (Fernández-Macías & Bisello, 2022). Detailed factor solutions are reported in Table A1.[4] To confirm the robustness of our latent constructs, we also performed an FA that included additional items that are not directly comparable between the datasets, but are still related to our underlying concepts. The results support our classification based on the comparable items only (see Online Supplement, Table S1). Distributions of each item for computer users and non-users are reported in Table 2. As the range of scales differs across items as well as countries (see Table 1), each item is normalized on a scale from 0 to 1 to increase comparability.

To operationalize occupational class position, we use one-digit codes from the 2008 International Standard Classification of Occupation (ISCO-08). For the main analysis, we use the differentiation between the salariat group (as defined in Erikson & Goldthorpe, 1992) and all other classes as the second category.[5] Different operationalizations yield similar results.

Adult training participation is measured as attendance at any job-related training within the 2 years prior to the interview for Germany. For the United Kingdom, it is measured based on whether a worker 'received instructions or training from someone that took them away from their normal job' or completed 'some other work-related training' in the previous 12 months.

As mentioned above, we include workers' educational attainment as a control variable. Educational attainment is measured using the 1997 revision of the International Standard Classification

TABLE 2 Mean and standard deviation of items of interests for computer users and non-users in Germany and the United Kingdom

The United Kingdom	User		Non-user		Germany	User		Non-user	
	Mean	SD	Mean	SD		Mean	SD	Mean	SD
Job satisfaction									
Satisfaction with					Satisfaction with				
the opportunity to use your abilities	0.76	0.19	0.70	0.22	type and content of work	0.75	0.20	0.70	0.20
being able to use your own initiative	0.77	0.18	0.73	0.21	opportunities for applying skills	0.72	0.22	0.68	0.23
this aspect of own job—the work itself	0.74	0.18	0.73	0.19	work on the whole	0.74	0.20	0.71	0.21
Job tasks									
Cognitive-analytical									
Importance of:									
spotting problems or faults	0.79	0.24	0.66	0.30	React to problems and solve them	0.85	0.25	0.70	0.32
working out causes of problems/ faults	0.74	0.26	0.58	0.32	Recognize and close your own gaps in knowledge	0.66	0.28	0.52	0.31
thinking of solutions to problems	0.78	0.24	0.57	0.32	Confronted with new tasks	0.77	0.25	0.62	0.31
					Improve existing procedures or try something new	0.68	0.27	0.56	0.31
Cognitive-interpersonal									
Importance of:									
counselling [. . .]	0.68	0.35	0.49	0.40	Purchasing, procuring, selling	0.33	0.40	0.27	0.38
dealing with people	0.91	0.18	0.78	0.28	Advertising, Marketing, Public Relations, PR	0.27	0.35	0.13	0.27
selling a product or service	0.46	0.39	0.30	0.38					
Physical									
Importance of:									
physical stamina	0.41	0.35	0.65	0.29	Work standing up	0.60	0.38	0.89	0.25
physical strength	0.34	0.34	0.64	0.30	Lift and carry heavy load	0.30	0.36	0.61	0.38

(Continues)

TABLE 2 (Continued)

The United Kingdom	User		Non-user		Germany	User		Non-user	
	Mean	SD	Mean	SD		Mean	SD	Mean	SD
Routine									
How much variety in job	0.28	0.26	0.46	0.32	Execution of work is prescribed in every detail	0.51	0.35	0.56	0.37
How often work involves short repetitive tasks	0.57	0.28	0.67	0.28	One and the same operation is repeated [. . .]	0.66	0.36	0.76	0.33
Task discretion									
Influence personally have on:									
how hard work	0.80	0.23	0.75	0.27	Plan and schedule your own work yourself	0.87	0.27	0.70	0.36
how to do the task	0.66	0.29	0.53	0.34	Influence the amount of work assigned to you	0.57	0.38	0.50	0.39
what tasks to do	0.75	0.26	0.64	0.32	Decide for yourself when to take a break	0.76	0.37	0.59	0.43
How much choice over the way in which job is done	0.71	0.26	0.63	0.31					
N	8595		2686			36,023		13,423	

Notes: All variables are normalized on a scale from 0 to 1, with higher values indicating higher levels of the latent construct of interest. Weighted. Original scales reported in Table 1.
Sources: Skills and Employment Survey (2006, 2012, 2017) for the United Kingdom; BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany; authors' calculations.

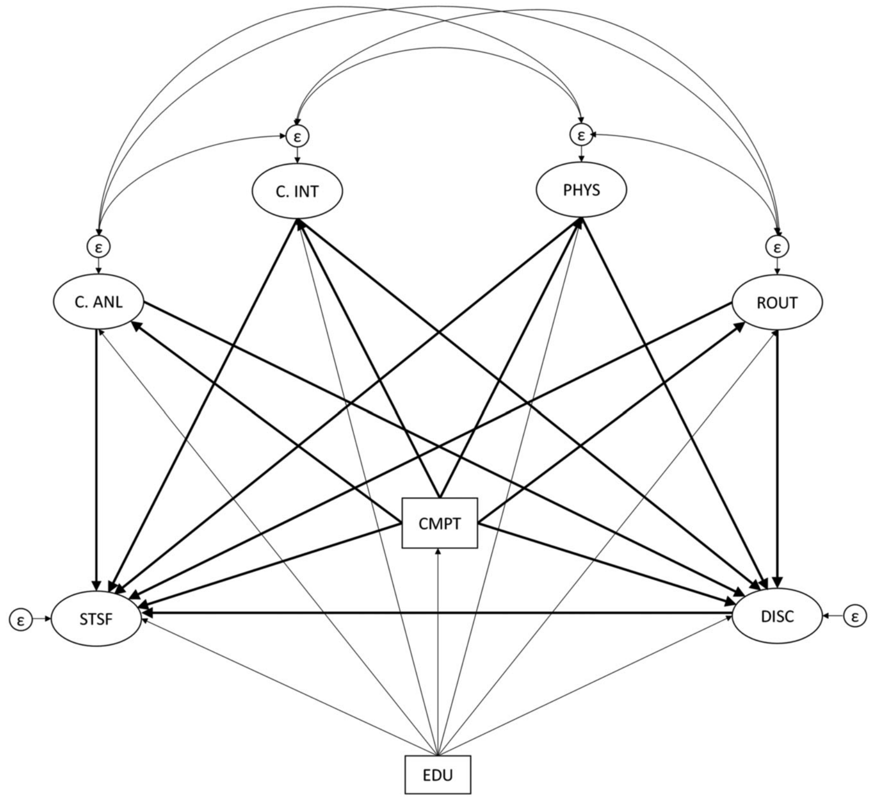

FIGURE 2 Empirical structural equation model. STSF, job satisfaction; C.ANL, cognitive-analytical tasks; C.INT, cognitive-interpersonal tasks; PHYS, physical tasks; ROUT, routine tasks; DISC, task discretion; CMPT, computer use at work; EDU, level of education.

of Education (ISCED). We distinguish between less-educated (ISCED 0–2), intermediate-educated (ISCED 3–4) and high-educated workers (ISCED 5+). We also consider a set of control variables in our robustness checks: industry captured by nine categories of the one-digit SIC92 classification for the United Kingdom and by 10 categories of the NACE rev 1 classification for Germany, gender as a dummy variable, age captured by three 15-year groups, ethnic background as a dummy variable, indicating non-white workers for the United Kingdom and migration background for Germany and survey year (three categories). Correlation matrices for all included variables are presented in the Online Supplement, Tables S2a and S2b.

5.2 | Methods

We test our theoretical model using structural equation modelling (SEM), as presented in Figure 2. Circled variables represent latent constructs. The underlying observed variables for each dataset are reported in Table 1. Squared variables are observed. The thick lines represent relationships that directly test our hypotheses and the theoretical model presented in Figure 1. Models are tested for each country separately on the yearly pooled sample as no major changes in the relationships of interest are expected across analysed years.[6]

Our SEM includes a correlation between the errors of the different job-task dimensions (which is theoretically supported by the fact that the different tasks required in an occupation are related), and the overall definition of a job is given by the *simultaneous* observation of all dimensions. We thus refrain from interpreting the mediating role of each single task index on task discretion and job satisfaction separately since the complementarity between computer use and job requirements is given by the overall task profile. To check for theoretically possible moderations by occupational class position and adult training participation, we estimate multi-group SEM models (Acock, 2013) for these sub-groups of workers. All models are estimated using maximum-likelihood estimation (Iacobucci, 2010).

Two major advantages of SEM for our study are: First, it allows both measurements and structural components to be included, which is critical because job satisfaction and skill requirements at work are not directly observed but obtained through latent constructs. This advantage also relaxes the issue of different item wordings across datasets. Second, SEM tests our theoretical model by including both structural paths and latent constructs on different data and contexts, and it compares the performances under different conditions. SEM thus enables to test whether theoretical path models of complex direct and indirect effects properly fit the data in the two countries analysed (e.g. Chin, 1998).

As highlighted by Bollen and Pearl (2013), the core of the SEM analysis involves specifying a theoretical model and subsequently testing whether this model is plausible given the observed data. SEM is a confirmatory approach that relies on translating theory into a statistical model. If the theoretical model is problematic and/or if empirical instruments are not accurate, the model will not be able to reproduce the data, and estimated parameters will not be interpretable, thereby casting doubt on the strong causal assumptions of zero coefficients or zero covariances. In other words, researchers do not obtain any causal relationship from SEM, SEM instead reflects and depends on researchers' theoretical assumptions about *possible and plausible* causal connections (Bollen & Pearl, 2013). In our study, the main assumption indicates the exogenous nature of computer use (Path 1 in Figure 1).[7]

Defining the theoretical foundations of a SEM model is even more relevant when disposable data on technological innovation take the form of cross-sectional surveys, as in our study, which leaves room for possible objections of endogeneity. It is, of course, possible and legitimate to argue that the changing nature of work towards more abstract and analytical cognitive content and procedures requires and/or favours the introduction of new technologies and computers in the workplace (thereby reversing Path 1 in our theoretical model). In other words, it is plausible that some occupations are more likely to adopt computerized equipment than others because of their task composition or level of discretion. However, the literature on technological adoption and skill requirements reviewed above has repeatedly considered technology as an exogenous factor influencing work content, not vice versa. Nevertheless, we cannot statistically rule out any endogeneity issue. For this reason, we refrain from making causal claims about the relationship between computers, tasks and task discretion. Instead, we refer more precisely to the existence of complementarity between computer use and skill requirements.

A crucial limitation of SEM is the difficulty in including numerous control variables to account for potential confounding factors,[8] which are usually considered in the analysis of the effects of computer use on skills and tasks at work (Green, 2012; Green et al., 2003; Menon et al., 2019). As a sensitivity analysis, we also estimated separate OLS regressions for all paths highlighted in the SEM model, including the aforementioned controls. This analysis confirms the results estimated via SEM (see Appendix, Tables A2a and A2b).

6 RESULTS

We begin with some descriptive findings and examine the average levels of task performance among computer users and non-users in the United Kingdom and Germany, as presented in Table 2 (see Section 5.2). While the performance of cognitive-analytical tasks is most pronounced (especially for computer users) in both countries, important differences exist regarding the use of the other three task subsets both within and between countries: In Germany, routine and physical tasks are relatively more frequent than cognitive-interpersonal tasks (among both computer users and non-users), which is exemplary of the technology-implementation processes in diversified quality production in German manufacturing, as discussed above. In the United Kingdom, cognitive-interpersonal tasks are more frequent than routine or physical tasks for computer users, whereas for non-users, the extent of physical tasks is greatest among these three subsets. Differences in job tasks between computer users and non-users are thus generally more pronounced in the United Kingdom than in Germany.

We now turn to our multivariate analysis. Table 3 presents the results of SEM for both the United Kingdom and Germany, decomposed into direct and total effects. Goodness-of-fit (GoF) statistics are included at the bottom of Table 3 to provide information on how well our model fits the data. The comparative fit index (CFI) indicates that our model improves the fit of a baseline model that assumes no covariances between items among latent variables. CFI in the United Kingdom is 0.954 and CFI in Germany was 0.929, suggesting an acceptable fit. Bentler and Bonett (1980) recommend a cut-off of 0.90 for some incremental fit indices, and a CFI over 0.90 is often considered acceptable (Jackson et al., 2009; McDonald & Ho, 2002). Hu and Bentler (1999) suggest a more restrictive limit of a CFI close to 0.95. Other authors have argued to relax this threshold, because a limit close to 0.95 might be too restrictive (Iacobucci, 2010; Marsh et al., 2004). Moreover, regarding the root mean square error of approximation (RMSEA), which adjusts for errors for each degree of freedom used, results are indicative of a good model fit, with values below or extremely close to the recommended upper bound of 0.05 (0.051 for the United Kingdom and 0.047 for Germany). Finally, we present the index of the standardized root mean square residual (SRMR) as a measure of how close our model comes on average to reproducing each correlation. In both countries, values are below the recommended cut-off of 0.05, which again confirms that our model fits the data well in both Germany and the United Kingdom (for details on GoF, see Acock, 2013 and Kyndt & Onghena, 2014). We therefore next discuss the presented results. Note that all variables except dichotomous ones are *z*-standardized.

We begin with our first research question—that is, the relationship between computer use and both job tasks and task discretion. The upper part of Table 3 presents estimates for Path 1 in our theoretical model and the association between computer use and our four factors/dimensions of job tasks (A–D). In Germany and the United Kingdom, computer use is clearly associated with higher levels of (analytical and interpersonal) cognitive tasks and lower levels of routine and physical tasks. These effects are statistically significant.[9]

One country difference emerges: The negative association between computer use and routine tasks appears to be larger in the United Kingdom than in Germany. The small(er) effect size for Germany might originate from the measurement of routine tasks performed in both surveys; however, this is the common form of measurement. Fernandez-Macias and Hurley (2016) criticize the concept of routine tasks proposed by the economic literature for its imprecise definition and introduce a further distinction between *routine tasks* (in terms of the level of cognitive or manual simplicity/sophistication) and *repetitive tasks* (in a temporal sense). In this respect, Frey and

TABLE 3 Direct and total effects of computer use on job tasks, task discretion and job satisfaction in the United Kingdom and Germany

	The United Kingdom		Germany	
	Direct effect	Total effect	Direct effect	Total effect
Path 1: Relationship between computer use and job tasks				
DV: Cognitive-analytical (A)				
Computer use	0.447***	n.i.p.	0.352***	n.i.p.
	(0.020)		(0.007)	
DV: Cognitive-interpersonal (B)				
Computer use	0.471***	n.i.p.	0.113***	n.i.p.
	(0.020)		(0.006)	
DV: Physical (C)				
Computer use	−0.529***	n.i.p.	−0.695***	n.i.p.
	(0.020)		(0.010)	
DV: Routine (D)				
Computer use	−0.213***	n.i.p.	−0.056***	n.i.p.
	(0.013)		(0.008)	
Paths 2 and 3: Relationship between computer use and task discretion (incl. mediation via tasks)				
DV: Task discretion				
Computer use	−0.034*	0.187***	0.085***	0.426***
	(0.015)	(0.015)	(0.012)	(0.009)
Cognitive-analytical	0.087***	n.i.p.	0.418***	n.i.p.
	(0.008)		(0.012)	
Cognitive-interpersonal	0.067***	n.i.p.	0.257***	n.i.p.
	(0.011)		(0.018)	
Physical	−0.022**	n.i.p.	−0.215***	n.i.p.
	(0.008)		(0.009)	
Routine	−0.653***	n.i.p.	−0.277***	n.i.p.
	(0.030)		(0.012)	
Paths 4, 5, 6: Relationship between computer use and job satisfaction (incl. mediation via tasks and discretion)				
DV: Job satisfaction				
Computer use	−0.122***	0.176***	−0.020	0.190***
	(0.022)	(0.022)	(0.012)	(0.009)
Cognitive-analytical	0.053***	0.094***	0.185***	0.289***
	(0.011)	(0.012)	(0.013)	(0.012)
Cognitive-interpersonal	0.027	0.059**	0.011	0.076***
	(0.016)	(0.017)	(0.017)	(0.017)
Physical	0.009	−0.001	−0.032**	−0.086***
	(0.012)	(0.013)	(0.010)	(0.010)
Routine	−0.828***	−1.144***	−0.260***	−0.329***
	(0.046)	(0.046)	(0.013)	(0.013)

(Continues)

TABLE 3 (Continued)

	The United Kingdom		Germany	
	Direct effect	Total effect	Direct effect	Total effect
Task discretion	0.483***	n.i.p.	0.251***	n.i.p.
	(0.025)		(0.012)	
Goodness-of-fit statistics				
CFI	0.954		0.929	
RMSEA	0.051		0.047	
SRMR	0.038		0.035	

Notes: All continuous variables are *z*-standardized (mean = 0, standard deviation = 1). Controlled for educational attainment. Standard errors in parentheses.

Abbreviations: DV, dependent variable; n.i.p., no indirect path included.

* $p < 0.05$;

** $p < 0.01$;

*** $p < 0.001$.

Sources: Skills and Employment Survey (2006, 2012, 2017) for the United Kingdom and BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany; authors' calculations.

Osborne (2017) identify finger- and manual dexterity characterized by the repetitive performance of hand- and finger accuracy as a potential bottleneck for automation. These tasks are thus *repetitive* but *not routine*. Our data do not allow for operationalizing this distinction; thus, our measure of routine tasks is likely conservative. Similarly, the somewhat larger association with physical tasks in Germany is likely driven by substitutions of routine- rather than non-routine physical tasks.

The middle of Table 3 reports estimates for the association between computer use and task discretion and integrates mediation via job tasks. Beginning with the direct effect of computer use on task discretion (i.e. net of computer-task complementarities and while capturing Path 3 in our theoretical scheme), important country differences can be observed: Computer use is associated with lower levels of task discretion in the United Kingdom (-0.034) but with higher levels in Germany (0.085). The same results emerge after including detailed controls for workforce composition (see Appendix, Tables A2a and A2b). Both effects are relatively small yet statistically significant. The total effect of computer use on task discretion (including both Paths 2 and 3) is positive and statistically significant in both countries, but larger in Germany. In the United Kingdom, 118 per cent of the total effect[10] is explained by mediation via job tasks (Path 2), which links the observed differences in task discretion between computer users and non-users to different tasks performed. In Germany, this mediation accounts for 80 per cent of the total effect, and estimates for the different task dimensions reveal that cognitive tasks are associated with higher levels of discretion, whereas routine and physical tasks are associated with lower levels. Effects are significant in both countries but considerably larger in Germany, except—again—for routine tasks. As mentioned above, we refrain from interpreting the indirect effects of computer use via each of the task indicators separately. In sum, the differences between the direct and total effects of computer use on task discretion reveal the importance of tasks as composite indicators of types of occupations and jobs that explain most variation between workers. The country differences found are indicative of the dissimilar production strategies that underlie these associations.

The total association between computer use and task discretion is strong and positive in both countries, suggesting that computer users, on average, not only perform less manual and more abstract tasks, but also have more control and autonomy over the content of their work and how they perform it. However, after we account for differences in task content between computer users and non-users—that is, the association between computer use and job discretion, net of job tasks—we observe a negative association in the United Kingdom but not in Germany. These results have two important implications for our hypothesis. First, in both countries, computers are conducive to a high level of discretion because they complement the performance of more abstract, cognitive and hence less monitorable tasks. Second, when we compare computer users and non-users performing similar tasks, we find hints of different employment strategies between the two countries, as computer users in the United Kingdom have less control over how they perform their work compared to non-users performing similar jobs. In other words, when considering two similar jobs in terms of task requirements in the United Kingdom, jobs performed with computerized equipment are characterized by a slightly lower level of discretion and autonomy than those performed without computerized equipment.

We now turn to our second research question—that is, the mediating role of job tasks and task discretion in the relationship between computer use and job satisfaction. Results are presented in the bottom of Table 3. The direct effect of computer use on job satisfaction—that is, independent of job tasks and task discretion (referring to Path 6 in Figure 1)—is negative in both countries (-0.117 in the United Kingdom and -0.020 in Germany). These direct effects are larger and statistically significant only in the United Kingdom. Once the role of job tasks and task discretion has been accounted for (via Paths 1–4, 3–5, and 1–2–5, respectively), the total effect of computer use on job satisfaction becomes positive and statistically significant in both countries (0.184 UK and 0.190 Germany). Mediation via the indirect paths of job tasks and task discretion accounts for 164 per cent of the total effect in the United Kingdom and 111 per cent in Germany. These results reveal the explanatory relevance that the associations between computer use, job tasks and task discretion have for job satisfaction.[11]

The overall positive association is completely due to higher levels of cognitive and abstract tasks, and consequently higher levels of task discretion. However, once we account for differences in job tasks and task discretion, we find a negative effect of computer use on job satisfaction in the United Kingdom and no effect in Germany. This negative direct effect, remaining above and beyond the mediation via job tasks and task discretion (our research focus), can be caused by many factors related to the use of technology itself (but not through its relationship to skill levels), one possible explanation is technostress (see discussion in Section 4).

Overall, the results confirm our theoretical expectation that complex job profiles and the possibility of controlling work processes should be positively associated with job satisfaction in both countries (see direct and total effects of job tasks and task discretion), thereby linking differences in task composition and task discretion between computer users and non-users to workers' job satisfaction. Country differences reflect the different skill- and production regimes, as discussed in the theoretical section. In the United Kingdom, mediation via job tasks—and particularly via routine tasks[12]—is much more pronounced than in Germany, which accounts for a substantial part of the total effects of computer use on both task discretion and job satisfaction. Differences in the levels of task discretion and job satisfaction by computer use, that remain net of the indirect paths via job tasks, are indicative of prevalent managerial practices in implementing and using computer technologies.

As discussed in Section 4, we are also interested in differences across groups of workers. We begin with multi-group comparisons of SEM between salariat workers and members of other occupational classes. Detailed results are presented in Table A3. In the United Kingdom, the observed *direct* effects of computer use on both task discretion and job satisfaction remain negative across all occupational classes but statistically significant only for non-salariat workers. Nevertheless, the positive *total* effects of computer use on both task discretion and job satisfaction are more pronounced for non-salariat than for salariat workers. As expected, these positive associations are determined by mediation via job tasks, with computer-task complementarities being most relevant to non-salariat workers.

For Germany, the alienating effect of computer use on job satisfaction is more pronounced among salariat than non-salariat workers, which also results in a smaller total effect that is still positive and statistically significant. In contrast, the positive *direct* effect of computer use on task discretion is larger among salariat workers. However, the positive *total* effect of computer use on task discretion is larger for non-salariat workers—most likely due to a stronger mediation via job tasks—and further reflects the large positive total effect on job satisfaction.

Second, we expected participation in adult training to intervene in the interplay between job tasks, task discretion, and job satisfaction. Results for this group-comparison SEM model are presented in Table A4. In both countries, the main group difference is observable for the direct negative effect of computer use on job satisfaction. In accordance with our theoretical considerations, an alienating effect of computer use is larger and statistically more relevant among non-trained than trained workers in both countries. Differences are somewhat more pronounced in Germany; however, we do not find empirical support for our expectation that the mediating effect of job tasks should be more positive for trained workers.

These results should be considered explorative because tests for group invariances of the parameters could not reject the null hypothesis of equality between occupational classes and between training groups. Moreover, as we only observed differences in the size but not in the direction of effects, these findings imply that our theoretical model of the relationship between technology and job satisfaction applies to different groups of workers, though to differing extents.

7 | CONCLUSIONS

Our comparative study on how computer use is associated with tasks performed at work and task discretion as two distinct dimensions of occupational skills in Germany and the United Kingdom—two exemplary cases of different production regimes and management practices—contributes both theoretically and empirically to the ongoing upskilling/de-skilling debate. Moreover, our study enhances the understanding of whether job tasks and task discretion mediate the relationship between technological innovation and job satisfaction. Generally, our results indicate that technology is not an entirely exogenous factor affecting the outcomes of implementation—in terms of job tasks, job discretion and workers' satisfaction with their working conditions—in a deterministic and unilateral way. Our study thereby highlights the different yet related issues of the complexity of the tasks performed and the degrees of work discretion.

In line with the RBTC thesis, our results suggest that in both countries, the use of computerized work equipment is complementary to less routine and more abstract tasks, while reducing physical and repetitive tasks. This complementarity is conducive to higher average levels of task discretion and workers' job satisfaction—consistent with an upskilling perspective.

However, after accounting for the association between computer use and job tasks, the direct effect of computer use on task discretion and workers' job satisfaction turns out to be different between the two countries and exemplary of the two different institutional regimes. Consistent with a de-skilling perspective, technology in the United Kingdom (an LME where firms have strong incentives to pursue production and employment strategies based on a flexible workforce with low firm attachment) is associated with lower levels of discretion and satisfaction, while in Germany, computer use is still positively associated with task discretion. In this way, the article contributes to the upskilling/de-skilling debate by suggesting that the association between computers and job satisfaction—after accounting for the fact that computers are adopted in jobs characterized by more abstract and cognitive tasks—is contingent on the 'context' in which technology is introduced. We argued that national institutional arrangements shaping firms' organizational structures and practices are a central factor influencing whether technology is adopted according to an upskilling or de-skilling logic. We employ ideas from production regimes theories that stress the importance of institutional incentives and constraints for employers to take up diverse employment strategies regarding skills demand and labour organization. This perspective does not capture all institutional differences between the two countries, thus other factors might also contribute to the country differences.

For example, authors using a power resources perspective characterize the German political economy as a dualistic regime, meaning that national institutional characteristics and power relations foster a polarization in several aspects of job quality between different labour market segments. Most common is the differentiation between (highly protected and high-skilled) primary and (low protection, low-skilled) secondary segments (Doeringer & Piore, 1971) or the labour market insider-outsider divide (Barbieri & Cutuli, 2016; Lindbeck & Snower, 1989). This perspective suggests that the implications of computer use may not only differ between countries but also within organizations. Our study focused on cross-national differences in the average association between computers, skills and work quality; however, existing differences between segments within countries affect these country differences by impacting on the overall association owing to compositional distribution of the different segments. In this respect, our analysis of group differences across types of occupations and access to training has not shown major differences. Starting from this analysis, future research could go deeper into how the relationships studied in this article differ across different labour market segments (as expressed, for example, by type of work contract).

Although our theoretical expectations are corroborated by empirical evidence, our study is not without limitations, which are mainly related to the nature of the available data. The main limit is the lack of standardized measurements of tasks and technological indicators between the two countries. Items on tasks and job content were differently worded in the two countries, and the survey question used to operationalize computer use differed (referring to the importance in the United Kingdom and the frequency in Germany). Nevertheless, descriptive evidence showed that computer use was similarly distributed across occupations, suggesting that despite differences in the wording, the indicator was comparable (see Online Supplement, Figure S1). Still, we cannot exclude that differences between the two countries are also partly due to measurement differences. Moreover, despite the vivid debate on technological change and the task content of jobs in the last decade, we still lack micro-level longitudinal and cross-country comparable data. It is therefore difficult to advance strong causal claims via an empirical analysis of cross-sectional data. Our paths are hence mainly driven by theoretical considerations. Consequently, one of the main issues that future research will have to tackle (using appropriate data) is that the relationship between computers and any potential outcome (e.g. wages, discretion or satisfaction) could be the result of occupational (or institutional) characteristics that simultaneously determine the use of technology and the content of work.

We have already discussed the limitations of operationalizing the routine-task dimension in existing surveys (see Section 6). Our findings for Germany suggest that future research and survey operationalization should better differentiate repetitive tasks in terms of frequency from routine tasks in terms of simplicity/sophistication. Not only are the two kinds of routine tasks distinct in terms of content, they also—at least theoretically—have different implications for the risk of being automated as well as for monitoring capacities. Future research may also pay attention to the remaining negative direct association between computer use and job satisfaction in the United Kingdom, after accounting for the relationship between computer use, tasks and task discretion. Technostress could be one explanation; other mechanisms could be in place as well.

Despite these limitations and given the established importance of technology for job content and workers' well-being, one of the key insights of this article is that it demonstrates the research potential that detailed, high quality, and comparable data sources on work content and technology usage, covering sufficient dimensions and indicators, would provide.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the Research Data Centre at BIBB (BIBB-FDZ) and the UK Data Service. Restrictions apply to the availability of these data, which were used under license for this study.

ETHICS STATEMENT

Not applicable because of use of secondary data.

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ENDNOTES

[1] It is important to clarify that the theory of RBTC mainly focuses on computer technologies that preceded the current wave of technological change, spurred by progress in artificial intelligence (Brynjolfsson & McAfee, 2014). Scholars suggest that, given recent advances in artificial intelligence and machine learning, the automating capacity of future technologies will go well beyond routine tasks (Arntz et al., 2016; Frey & Osborne, 2017).

[2] The economic literature usually identifies a rise in low-skilled jobs in Europe and the United States and a growth in low-skilled janitorial services, which echoes the sociological thesis of the so-called *service proletariat* (Esping-Andersen, 1993). Bernardi and Garrido (2008) have shown evidence of a U-shaped polarization for Spain; however, Fagan et al. (2005) report notable skill differences in the occupational structure of manual services between Germany and the United Kingdom, with a higher level of manual-workforce qualification in the German service sector. It follows that *non-automatable, non-routine manual/physical tasks* may differ between the two countries. Unfortunately, disposable data do not allow for properly distinguishing between these differences.

[3] The UK sample does not include the Highlands and Islands, and Northern Ireland.

[4] One potential issue is whether the items used in the two countries (and therefore the latent constructs derived from them) are cross-culturally comparable. As shown by both exploratory and confirmatory FA, items in each

country belong to comparable theoretical constructs, supporting confidence in our latent concepts. Moreover, they are drawn from the only disposable data sources containing all necessary information to properly investigate our theoretical model. Thus, even though differences in item wordings might blur cross-country differences in the magnitude of the relationships, observed cross-country differences in the direction of the relationships are unlikely to be the result of measurements errors, since items belong to the same domain.

[5] Armed-forces occupations are excluded.

[6] We also tested the multiple-group SEM for each year. The Wald test could not reject the null hypothesis of equality in the parameters of interest. Furthermore, we estimated OLS regressions for each path of interest, including the survey wave as a control variable (see Online Supplement, Tables S3a and S3b).

[7] For a recent discussion on technology as the exogenous driver behind new forms of work and on the effects of new technologies on the future of work and skills, see: "The changing nature of work and skills in the digital age" (European Union, 2019).

[8] Given the large number of control variables (and numerous subcategories), their inclusion in the SEM model would require the specification of a large number of parameters connecting each category of the exogenous variables to all the outcomes, and possibly also correlations between exogenous variables. This would result in an overly complex model, which would be hard to fit and interpret. Instead, we fit a more parsimonious model representing the core relationships and including educational level as a control. In a second step, we test the key relationship including detailed control variables through separate OLS regressions (see Appendix, Tables A2a and A2b).

[9] Reported standard errors are non-robust; however, applying robust standard errors, the same coefficients remain significant according to conventional thresholds and thus do not alter our conclusions.

[10] The percentage mediated is computed as the total effect minus the direct effect, divided by the total effect. Percentages higher than 100 are due to negative direct effects and positive total effects.

[11] As a robustness check, we estimated OLS regressions that accounted for demographic, occupational and industrial differences between computer users and non-users. The total effect of computer use on the degree of job satisfaction was found to decrease in the United Kingdom and to no longer be significant, while the negative direct effect remained significant (see Appendix, Table A2a). In Germany, the already small negative direct effect approximated zero and remained non-significant (see Appendix, Table A2b).

[12] Routine tasks in the United Kingdom have by far the largest direct and total effect on job satisfaction; however, the negative direct effect of computer use is robust after excluding the routine-task indicator from the SEM model.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX

A1, A2a, A2b, A3 and A4

TABLE A1 Factor analysis of comparable skills items for the United Kingdom and Germany

	C.ANL	DISCRET	PHYS	C.INT	ROUT	Uniq.
The United Kingdom						
Importance of						
… working out causes of problems	0.925					0.132
… spotting problems	0.892					0.198
… thinking of solutions to problems	0.847					0.219
Influence personally have on						
… what task to do		0.806				0.302
… how to do the tasks		0.793				0.333
… how hard to work		0.714				0.462
How much choice have over way in which job is done		0.675				0.438
Importance of						
… physical stamina			0.941			0.108
… physical strength			0.935			0.114
… counselling, and advising				0.812		0.311
… dealing with people				0.742		0.390
… selling a product of service				0.683		0.479
How often work involves short and repetitive tasks					0.819	0.297
How much variety in job					0.681	0.354
Eigenvalues	*3.690*	*2.095*	*1.583*	*1.469*	*1.028*	
Germany	**C.ANL**	**PHYS**	**DISCRET**	**ROUT**	**C.INT**	**Uniq.**
Confronted with new tasks	0.740					0.430
Recognize and close your own gaps in knowledge	0.688					0.508
React to problems and solve them	0.682					0.506
Improve existing procedures or try something new	0.645					0.498
Work standing up		0.858				0.254
Lift and carry heavy load		0.827				0.300
Influence the amount of work assigned to you			0.745			0.409
Plan and schedule your own work yourself			0.689			0.425
Decide for yourself when to take a break			0.644			0.481

(Continues)

TABLE A1 (Continued)

Germany	C.ANL	PHYS	DISCRET	ROUT	C.INT	Uniq.
Execution of work is prescribed in every detail				0.812		0.282
One and the same operation is repeated in every detail				0.799		0.296
Purchasing, procuring, selling					0.822	0.292
Advertising, Marketing, Public Relations, PR					0.748	0.360
Eigenvalues	*2.934*	*1.622*	*1.253*	*1.113*	*1.038*	

Notes: Factor loadings estimated using the principal-component-factor method. Orthogonal rotation applied. Weighted. Blanks represent abs(loadings) < 0.35.
Abbreviations: C.ANL, cognitive-analytical tasks; DISCRET, task discretion; PHYS, physical tasks; C.INT, cognitive-interpersonal tasks; ROUT, routine tasks;
Sources: Skills and Employment Survey (2006, 2012, 2017) for the United Kingdom and BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany; authors' calculations.

TABLE A2a The United Kingdom—OLS regressions of total and direct effects of computer use on discretion and satisfaction

	Total effect on discretion	Direct effect on discretion	Total effect on satisfaction	Direct effect on satisfaction
Computer use	0.096**	−0.065^{+}	0.045	−0.084*
	(0.035)	(0.033)	(0.037)	(0.036)
Task indicators				
Cognitive-analytical		0.157***		0.091***
		(0.013)		(0.012)
Cognitive-interpersonal		0.098***		0.030*
		(0.013)		(0.014)
Physical		−0.006		0.022
		(0.014)		(0.014)
Routine		−0.242***		−0.241***
		(0.013)		(0.014)
Discretion				0.313***
				(0.013)
Educational attainment (reference: less-educated (ISCED 0–2))				
Intermediately educated (ISCED 3–4)	0.138***	0.104**	−0.095**	−0.159***
	(0.036)	(0.035)	(0.036)	(0.033)
Highly educated (ISCED 5+)	0.122**	0.041	−0.223***	−0.328***
	(0.040)	(0.038)	(0.042)	(0.039)

(Continues)

TABLE A2a (Continued)

	Total effect on discretion	Direct effect on discretion	Total effect on satisfaction	Direct effect on satisfaction
Occupation (reference: managers)				
Professionals	−0.376***	−0.312***	−0.057	0.093*
	(0.035)	(0.035)	(0.041)	(0.038)
Technicians and associate professionals	−0.455***	−0.360***	−0.163***	0.049
	(0.038)	(0.037)	(0.041)	(0.038)
Clerical-support workers	−0.653***	−0.408***	−0.423***	−0.023
	(0.044)	(0.043)	(0.049)	(0.043)
Service- and sales workers	−0.693***	−0.487***	−0.372***	−0.007
	(0.040)	(0.040)	(0.046)	(0.044)
Skilled agriculture-, forestry-, and fishery workers	−0.399*	−0.254+	−0.139	0.067
	(0.155)	(0.143)	(0.239)	(0.231)
Craft- and related-trades workers	−0.604***	−0.494***	−0.184***	0.042
	(0.049)	(0.050)	(0.051)	(0.049)
Plant- and machine operators and assemblers	−1.092***	−0.767	−0.601***	−0.042
	(0.064)	(0.062)	(0.063)	(0.060)
Elementary occupations	−0.935***	−0.560***	−0.698***	−0.163*
	(0.054)	(0.058)	(0.061)	(0.064)
Further-training participation	0.071**	−0.011	0.052*	−0.028
	(0.023)	(0.022)	(0.026)	(0.024)
Constant	0.502	0.541	0.342	0.19
	(0.140)	(0.127)	(0.205)	(0.169)
Observations	11,281	11,281	11,281	11,281
R^2	0.139	0.225	0.073	0.258

Notes: All continuous index variables are predicted scores from a separate factor analysis for each latent construct (see Table A1). Controlled for industry, age, gender, ethnic background and survey year. Weighted. Robust standard errors in parentheses.
Abbreviation: ISCED, International Standard Classification of Education.
+ $p < 0.1$;
* $p < 0.05$;
** $p < 0.01$;
*** $p < 0.001$.
Sources: Skills and Employment Survey (2006, 2012, 2017); authors' calculations. Full results in Table S3a of the Online Supplement.

TABLE A2b Germany—OLS regressions of total and direct effects of computer use on discretion and satisfaction

	Total effect on discretion	Direct effect on discretion	Total effect on satisfaction	Direct effect on satisfaction
Computer use	0.225***	0.121***	0.093***	0.006
	(0.017)	(0.017)	(0.016)	(0.016)
Task indicators				
Cognitive-analytical		0.194***		0.088***
		(0.007)		(0.008)

(Continues)

TABLE A2b (Continued)

	Total effect on discretion	Direct effect on discretion	Total effect on satisfaction	Direct effect on satisfaction
Cognitive-interpersonal		0.113***		0.020**
		(0.006)		(0.006)
Physical		−0.090***		−0.067***
		(0.007)		(0.007)
Routine		−0.140***		−0.117***
		(0.006)		(0.006)
Discretion				0.160***
				(0.007)
Educational attainment (reference: less-educated (ISCED 0–2))				
Intermediately educated (ISCED 3–4)	0.177***	0.132***	−0.136***	−0.181***
	(0.033)	(0.032)	(0.031)	(0.031)
Highly educated (ISCED 5+)	0.302***	0.142***	−0.208***	−0.345***
	(0.035)	(0.033)	(0.034)	(0.034)
Occupation (reference: managers)	0.177***	0.132***		
Professionals	−0.249***	−0.203***	−0.060*	−0.022
	(0.020)	(0.020)	(0.030)	(0.029)
Technicians and associate professionals	−0.316***	−0.134***	−0.216***	−0.083**
	(0.020)	(0.020)	(0.030)	(0.030)
Clerical-support workers	−0.456***	−0.207***	−0.373***	−0.181***
	(0.024)	(0.024)	(0.034)	(0.033)
Service- and sales workers	−0.497***	−0.263***	−0.291***	−0.078*
	(0.027)	(0.027)	(0.036)	(0.035)
Skilled agriculture-, forestry-, and fishery workers	−0.462***	−0.142*	−0.124	0.127
	(0.071)	(0.068)	(0.076)	(0.078)
Craft- and related-trades workers	−0.705***	−0.381***	−0.289***	−0.013
	(0.027)	(0.028)	(0.035)	(0.035)
Plant- and machine operators and assemblers	−0.919***	−0.504***	−0.496***	−0.149***
	(0.034)	(0.035)	(0.040)	(0.040)
Elementary occupations	−0.891***	−0.402***	−0.612***	−0.232***
	(0.040)	(0.040)	(0.044)	(0.045)
Further-training participation	0.172***	0.089***	0.170***	0.108***
	(0.013)	(0.012)	(0.013)	(0.013)
Constant	0.227***	0.159**	0.240***	0.163**
	(0.052)	(0.051)	(0.058)	(0.057)
Observations	49,446	49,446	49,446	49,446
R^2	0.153	0.220	0.046	0.101

Notes: All continuous index variables are predicted scores from a separate factor analysis for each latent construct (see Table A1). Controlled for industry, age, gender, ethnic background and survey year. Weighted. Robust standard errors in parentheses.

* $p < 0.05$;

** $p < 0.01$;

*** $p < 0.001$.

Sources: BIBB/BAuA Employment Survey (2006, 2012, 2018); authors' calculations. Full results in Table S3b of the Online supplement.

TABLE A3 Structural equation modelling (SEM) of direct and total effects of computer use on job tasks, task discretion and job satisfaction, separated by occupational class position, including tests for the parameter invariance of direct effects

	The United Kingdom				Germany			
	Lower ESeC		Higher ESeC		Lower ESeC		Higher ESeC	
	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect
DV: Cognitive-analytical tasks								
Computer use	0.403***	*No Ind. Path*	0.338***	*No Ind. Path*	0.126***	*No Ind. Path*	0.352***	*No Ind. Path*
	(0.023)		(0.059)		(0.010)		(0.010)	
DV: Cognitive-interpersonal tasks								
Computer use	0.420***	*No Ind. Path*	0.069	*No Ind. Path*	0.035*	*No Ind. Path*	0.201***	*No Ind. Path*
	(0.024)		(0.063)		(0.014)		(0.010)	
DV: Physical tasks								
Computer use	−0.473***	*No Ind. Path*	−0.519***	*No Ind. Path*	−0.659***	*No Ind. Path*	−0.737***	*No Ind. Path*
	(0.023)		(0.071)		(0.020)		(0.011)	
DV: Routine tasks								
Computer use	−0.111***	*No Ind. Path*	−0.098**	*No Ind. Path*	0.025	*No Ind. Path*	0.006	*No Ind. Path*
	(0.011)		(0.034)		(0.016)		(0.012)	
DV: Task discretion								
Computer use	−0.047**	0.113***	−0.061	0.062	0.060***	0.246***	0.042*	0.394***
	(0.017)	(0.017)	(0.045)	(0.046)	(0.013)	(0.011)	(0.018)	(0.013)
Cognitive-analytical	0.109***	*No Ind. Path*	0.065***	*No Ind. Path*	0.145***	*No Ind. Path*	0.488***	*No Ind. Path*
	(0.011)		(0.013)		(0.017)		(0.017)	
Cognitive-interpersonal	0.067***	*No Ind. Path*	0.080***	*No Ind. Path*	0.264***	*No Ind. Path*	0.236***	*No Ind. Path*
	(0.013)		(0.022)		(0.015)		(0.023)	
Physical	−0.011	*No Ind. Path*	−0.062***	*No Ind. Path*	−0.244***	*No Ind. Path*	−0.183***	*No Ind. Path*
	(0.010)		(0.014)		(0.010)		(0.014)	
Routine	−0.738***	*No Ind. Path*	−0.641***	*No Ind. Path*	−0.100***	*No Ind. Path*	−0.363***	*No Ind. Path*
	(0.046)		(0.053)		(0.011)		(0.017)	

(Continues)

TABLE A3 (Continued)

	The United Kingdom				Germany			
	Lower ESeC		Higher ESeC		Lower ESeC		Higher ESeC	
	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect
DV: Job satisfaction								
Computer use	−0.110***	0.111***	−0.109	−0.014	−0.038	0.059**	−0.025	0.182***
	(0.025)	(0.025)	(0.061)	(0.065)	(0.022)	(0.019)	(0.016)	(0.011)
Cognitive-analytical	0.071***	0.130***	0.043*	0.071***	0.174***	0.262***	0.232***	0.322***
	(0.015)	(0.016)	(0.017)	(0.018)	(0.030)	(0.029)	(0.016)	(0.014)
Cognitive-interpersonal	0.053**	0.090***	−0.007	0.027	<u>−0.070*</u>	0.091***	<u>0.006</u>	0.050*
	(0.018)	(0.020)	(0.027)	(0.030)	(0.029)	(0.024)	(0.020)	(0.020)
Physical	<u>−0.024</u>	−0.031*	<u>0.059**</u>	0.033	<u>0.101***</u>	−0.047**	<u>−0.071***</u>	−0.105***
	(0.014)	(0.015)	(0.018)	(0.021)	(0.020)	(0.015)	(0.012)	(0.012)
Routine	−0.866***	−1.269***	−0.868***	−1.151***	<u>−0.249***</u>	−0.310***	<u>−0.180***</u>	−0.247***
	(0.066)	(0.072)	(0.079)	(0.083)	(0.018)	(0.018)	(0.015)	(0.015)
Task discretion	<u>0.546</u>	*No Ind. Path*	<u>0.439***</u>	*No Ind. Path*	<u>0.610***</u>	*No Ind. Path*	<u>0.185***</u>	*No Ind. Path*
	(0.030)		(0.039)		(0.048)		(0.014)	
Goodness-of-fit statistics								
CFI	0.954				0.921			
RMSEA	0.048				0.047			
SRMR	0.039				0.038			

Notes: Underlined coefficient estimates indicate rejection of the null hypothesis of equality between groups. All continuous variables are z-standardized to have a mean of 0 and a standard deviation of 1. Controlled for educational attainment. Standard errors in parentheses.

Abbreviation: DV, dependent variable.

*$p < 0.05$;

** $p < 0.01$;

*** $p < 0.001$.

Sources: Skills and Employment Survey (2006, 2012, 2017) for the United Kingdom and BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany; authors' calculations.

TABLE A4 Structural equation modelling (SEM) of direct and total effects of computer use on job tasks, task discretion and job satisfaction, separated by training participation, including tests for the parameter invariance of direct effects

	The UK				Germany			
	Trained		Non-trained		Trained		Non-trained	
	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect
DV: Cognitive-analytical tasks								
Computer use	0.217***	*No Ind. Path*	0.501***	*No Ind. Path*	0.175***	*No Ind. Path*	0.430***	*No Ind. Path*
	(0.033)		(0.025)		(0.008)		(0.013)	
DV: Cognitive-interpersonal tasks								
Computer use	0.211***	*No Ind. Path*	0.513***	*No Ind. Path*	0.067***	*No Ind. Path*	0.152***	*No Ind. Path*
	(0.033)		(0.027)		(0.007)		(0.010)	
DV: Physical tasks								
Computer use	−0.637***	*No Ind. Path*	−0.496***	*No Ind. Path*	−0.652***	*No Ind. Path*	−0.798***	*No Ind. Path*
	(0.037)		(0.025)		(0.013)		(0.015)	
DV: Routine tasks								
Computer use	−0.207***	*No Ind. Path*	−0.181***	*No Ind. Path*	−0.000	*No Ind. Path*	−0.097***	*No Ind. Path*
	(0.024)		(0.016)		(0.008)		(0.012)	
DV: Task discretion								
Computer use	−0.033	0.121***	−0.037	0.198***	0.096***	0.302***	0.067**	0.487***
	(0.025)	(0.024)	(0.020)	(0.019)	(0.014)	(0.011)	(0.023)	(0.016)
Cognitive-analytical	0.070***	*No Ind. Path*	0.100***	*No Ind. Path*	0.377***	*No Ind. Path*	0.424***	*No Ind. Path*
	(0.012)		(0.012)		(0.019)		(0.019)	
Cognitive-interpersonal	0.043*	*No Ind. Path*	0.084***	*No Ind. Path*	0.233***	*No Ind. Path*	0.264***	*No Ind. Path*
	(0.018)		(0.014)		(0.021)		(0.032)	
Physical	−0.012	*No Ind. Path*	−0.030**	*No Ind. Path*	−0.190***	*No Ind. Path*	−0.199***	*No Ind. Path*
	(0.012)		(0.012)		(0.011)		(0.017)	
Routine	−0.595***	*No Ind. Path*	−0.701***	*No Ind. Path*	0.067***	*No Ind. Path*	−0.400***	*No Ind. Path*
	(0.041)		(0.043)		(0.023)		(0.025)	

(Continues)

TABLE A4 (Continued)

	The UK				Germany			
	Trained		Non-trained		Trained		Non-trained	
	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect
DV: Job satisfaction								
Computer use	−0.089*	0.123***	−0.133***	0.170***	−0.012	0.106***	−0.049*	0.214***
	(0.036)	(0.037)	(0.029)	(0.029)	(0.015)	(0.012)	(0.021)	(0.015)
Cognitive-analytical	0.056***	0.087***	0.057***	0.107***	0.179***	0.283***	0.174***	0.266***
	(0.017)	(0.018)	(0.016)	(0.017)	(0.021)	(0.020)	(0.019)	(0.018)
Cognitive-interpersonal	0.012	0.030	0.041*	0.082***	0.005	0.069**	−0.009	0.049
	(0.026)	(0.028)	(0.020)	(0.022)	(0.021)	(0.021)	(0.029)	(0.029)
Physical	0.048**	0.042*	−0.014	−0.030	<u>−0.004</u>	−0.056***	<u>−0.066</u>***	−0.109***
	(0.017)	(0.018)	(0.016)	(0.018)	(0.012)	(0.011)	(0.017)	(0.016)
Routine	−0.843***	−1.102***	−0.818***	−1.167***	<u>−0.222</u>***	−0.287***	<u>−0.313</u>***	−0.400***
	(0.066)	(0.065)	(0.064)	(0.066)	(0.014)	(0.014)	(0.024)	(0.023)
Task discretion	0.435***	*No Ind. Path*	0.498***	*No Ind. Path*	<u>0.276</u>***	*No Ind. Path*	<u>0.217</u>***	*No Ind. Path*
	(0.039)		(0.033)		(0.017)		(0.018)	
Goodness-of-fit statistics								
CFI	0.954				0.921			
RMSEA	0.05				0.047			
SRMR	0.04				0.036			

Notes: Underlined coefficient estimates indicate rejection of the null hypothesis of equality between groups. All continuous variables are z-standardized to have a mean of 0 and a standard deviation of 1. Controlled for educational attainment. Standard errors in parentheses.

Abbreviation: DV, dependent variable.

* $p < 0.05$;

** $p < 0.01$;

*** $p < 0.001$.

Sources: Skills and Employment Survey (2006, 2012, 2017) for the United Kingdom and BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany; authors' calculations.