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The Impact of Digital Technologies on Skills-to-Job Mismatches

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Correspondence: Ana Santiago-Vela (santiagovela@bibb.de)**Received:** 16 July 2024 | **Revised:** 13 May 2026 | **Accepted:** 11 June 2026**Keywords:** computers | digital technologies | digitalization | entropy balancing re-weighting approach | organizational context | skill requirements | skills-to-job mismatch | technological change | upskilling | workplace

ABSTRACT

A pervasive discourse calls for worker upskilling amid ongoing digital transformation. This study introduces a skills-to-job mismatch perspective into research on the digital transformation of work by conceptualising technological adoption as a process that reshapes the relationship between workers' skill endowments and evolving job requirements. To empirically address this perspective, the study combines German individual- and establishment-level data with an entropy balancing method. The findings reveal that adopting new digital technologies in the workplace is associated with greater underskilling and reduced overskilling (i.e., skill underutilisation). Furthermore, effect heterogeneity emerges across the level of digitalisation in economic sectors. Technology adoption is more strongly associated with lower overskilling in less digitally mature sectors, while the positive association with underskilling is evenly distributed across sectors. Overall, this study provides a theoretically grounded framework and an informed empirical basis for a more nuanced debate on the digital transformation of work.

1 | Introduction

The impact of digital technologies on the labour market remains a cornerstone of academic and policy discourses, with renewed interest spurred by recent developments in artificial intelligence systems such as ChatGPT. Previous studies on technological progress have used the well-established frameworks of skill-biased technological change (SBTC) and routine-biased technological change (RBTC). Although differing in their predictions—RBTC anticipates a polarisation in employment—both frameworks consider that technological progress places greater demands on skills levels (Card and DiNardo 2002; Spitz-Oener 2006; Goos and Manning 2007; Michaels et al. 2010; Autor et al. 2020). Accordingly, policy discourses predominantly advocate for the upskilling of the workforce in order to navigate these technological changes effectively (Schlogl et al. 2021).

However, robust evidence on how technological progress affects the relationship between workforce skills and skill requirements remains scarce, often relying on implicit and indirect assumptions. This study aims to fill this gap by examining the impact of the introduction of new digital technologies in the workplace on the match between workers' skills and workplace requirements. It analyses the concept of skills-to-job mismatches as a result of workplace digitalisation. In capturing (im)balances between the skills supply of workers and the skills demands of workplaces, skills-to-job (mis)matches the heart of academic debates on the rapid digital transformation of skills and work and the consequent implementation of policies tailored to digital transformation.

This study investigates the relationship between the introduction of digital technologies in German workplaces and self-reported underskilling and overskilling. These terms refer to situations in which workers report their overall skill endowments to be lower

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(underskilling) or higher (overskilling) than the overall level of skills required for their job. In addition, it examines whether this relationship varies depending on companies' existing level of digital technology across different economic sectors. This sector-specific perspective is informed by labour market segmentation approaches, which emphasise the heterogeneity of the labour market across sectors (Doeringer and Piore 1971; Sengenberger 1981; Lindbeck and Snower 1986). In so doing, this study takes into account the reorganisation of work in holistic organisations that enhance learning across tasks (Lindbeck and Snower 2000) and the embeddedness of technology adoption in organisational contexts (Ohlert et al. 2022).

We applied an entropy balancing method (Hainmueller 2012; Hainmueller and Xu 2013) and created an integrated dataset containing microdata from the German BIBB/BAuA Employment Survey 2018 (Hall et al. 2020) and establishment data from the German BIBB Training Panel 2018 (Gerhards et al. 2022). Our analyses capture technology adoption by the introduction of digital technologies in the workplace and by the existing level of digital technologies in companies (i.e. the usage of digital technologies within establishments), instead of relying on the more common proxy of the substitution potential of occupations (Frey and Osborne 2017; Kortmann et al. 2022). Against the background that digitalisation has increasingly come to describe the transformation of work and economic activity through the adoption of digital technologies (Loebbecke and Picot 2015), we understand digitalisation as the implementation of digital technologies that alter work organisation and task structures. Thus, digitalisation is operationalised along these two dimensions: the introduction of new computer programmes in the workplace and the broader diffusion of digital technologies across companies in different sectors.

Following the frameworks commonly used to study technological change in the economic and social sciences, there has been limited engagement with transparent and concise conceptualisations of the skills that people bring to jobs and the skills that jobs require (Spenner 1990). While some studies rooted in human capital theory and Mincer (1974) earnings model use skills and education interchangeably (Autor et al. 1998; Dauth et al. 2017), other studies following the task-based approach rely on the tasks content of jobs to capture skill requirements (Spitz-Oener 2006; Autor and Handel 2013). This makes it challenging to conceptualise workers' skills and job requirements separately. The present study goes beyond the task-based approach (Autor et al. 2003) by engaging with a more precise distinction between skill requirements and skill endowments. Although education plays a pivotal role in the acquisition of skills and in the subsequent performance of tasks, the common strategy of using education or tasks as a proxy for skill requirements and endowments can lead to biased results (Green et al. 2003) and is also problematic for several reasons. First, it omits the dynamic nature of skills; skills increase with training and experience and depreciate when they are not put to the right use at work (Ferreira et al. 2017). Second, this strategy ignores that same-level education programmes may differ substantially in terms of content and quality (Esposito 2008; Lindley and McIntosh 2015; Britton et al. 2022). This argument, extensively developed in the occupational closure literature (Weeden 2002; Bol and Weeden 2015; Giesecke et al. 2020), is

particularly relevant in the highly vocationalised education system in Germany, where the content of same-level educational programmes determines labour market positions (Solga and Konietzka 1999). Third, comparing the levels of skills required to perform different tasks presents a major, unresolved analytical challenge (Martinaitis et al. 2021). Lastly, it ignores skills-to-job mismatches—when the skills that people bring to jobs (understood as individual-level endowments such as knowledge, abilities or capacities) do not necessarily match the skills that are required to perform certain tasks in the workplace (Spenner 1983, 1990).

In addition, this study introduces several innovative perspectives into the analysis of digital technologies and skills. First, we argue that technology needs to be understood as a process that continually throws up challenges in the workplace. Previous research has focused on predicting what types of jobs and skills will be more affected by technological change in the future (Gekara and Thanh Nguyen 2018). Fluidity is intrinsic to technological change and should be incorporated into our understanding of skill requirements (Green 2013). Focusing on skills mismatches consistently captures the need for workers to continuously develop their knowledge and skills (Allen and de Grip 2008; Nedelkoska and Quintini 2018).

Second, in addition to the mainstream approach which urges workers to upskill (Schlogl et al. 2021) in response to the expected increasing of underskilling from digitalisation, this study complements the existing evidence by integrating the other mismatch side—overskilling. When workers are overskilled, they underutilise their skills, which can lead to cognitive decline (De Grip et al. 2008). There is a lack of evidence on the relationship between overskilling and technological change. If new technologies could contribute to avoiding this detrimental phenomenon, this would add some positive nuance into the debate on the effects of technological change on workers.

Third, measuring the introduction of digital technologies adds to the scarce evidence measuring digital technologies (Genz et al. 2019) and improves upon indirect measures of automation potentials based on job tasks, education-specific wages or direct measures of industry-specific technologies such as robots (Acemoglu and Restrepo 2020; Graetz and Michaels 2018; Genz et al. 2019; Antón et al. 2022; Damelang and Otto 2023).

Fourth, this study focuses on technology adoption at the workplace level, extending the important yet under-researched evidence on the transformation of workplaces that do not neglect digitalisation-driven effects within workplaces (Spitz-Oener 2006; Hardy et al. 2018; Freeman et al. 2020; Fernández-Macías et al. 2022). While numerous scholars have followed the prominent work of Autor et al. (2003) on the automation of routine tasks by digital technologies, the majority of them have used information at the occupational level to assess employment changes or focused on industry or country-specific differences, rather than considering that jobs are often transformed and not completely eliminated by technology (Lloyd and Payne 2023). Using information at the occupational level also ignores the important within-occupation heterogeneity (La Rica et al. 2020) and considers workers and workplaces covered by the same occupational category as identical in

terms of tasks and skills (Holm and Lorenz 2022; Lloyd and Payne 2019).

We propose that within the context of digital transformation, it is advantageous to shift the analytical focus from debates centred on automation and job task within the frameworks of RBTC and SBTC towards an examination of skills-to-job mismatches. The advent of sophisticated technological innovations, exemplified by generative artificial intelligence such as ChatGPT, has the effect of reshaping the nature of ostensibly human-exclusive creative tasks that were previously considered immune to automation (Autor 2024; Brynjolfsson and McAfee 2011; Brynjolfsson and Mitchell 2017).

2 | Digital Technologies, Workplace Requirements and Skills (Mis)Matches: Theoretical Perspectives and Hypotheses

SBTC posits that technological advancements engender an increased demand for skilled labour, anticipating a shift towards a greater need for highly skilled workers. Conversely, RBTC focuses on the nature of job tasks and suggests that routine tasks are increasingly vulnerable to technological automation. As routine tasks are mostly performed by mid-skilled workers (Acemoglu and Autor 2011; Goos et al. 2014), higher- and lower-skilled jobs will increase their employment shares to the detriment of middle-skilled jobs, leading to a polarised employment structure. Though polarisation has been amply studied, recent research has questioned whether the RBTC hypothesis alone can fully explain labour market developments in Germany. Evidence points to the limited explanatory power of occupational routine content (Fernández-Macías and Hurley 2017; Walo 2023), partly due to inconsistencies in how it is conceptualised and operationalised (Fernández-Macías and Bisello 2022; Haslberger 2022). Moreover, structural de-routinisation may coexist with increasing routinisation within occupations, complicating interpretations of polarisation (Fernández-Macías et al. 2022). Findings for Germany underscore the need for a more nuanced view of polarisation (Fernández-Macías and Hurley 2017; Oesch and Piccitto 2019), with studies identifying a pattern of polarised upgrading (Spitz-Oener 2006) or a more moderately polarised upgrading (Oesch and Rodríguez Menes 2011; Oesch and Piccitto 2019; Sarkar 2017).

A common feature of both SBTC and RBTC frameworks is that they have principally been used to elucidate the effects of technological advancements on wage dynamics and employment structures. However, the relationships between the skills of the workforce and the skill requirements of jobs have only been implicitly analysed or have remained overlooked. Although the dynamics of employment, occupations and tasks and educational upgrading in employment have been extensively studied, the causal relationship between the introduction of new technologies and shifts at the workplace level has largely gone unaddressed. An analytical framework incorporating the concept of skills-to-job mismatches could more accurately reflect the evolving and dynamic nature of skill requirements in a rapidly changing labour market.

This study aims to reconcile two strands of research—the labour market effects of technological change and the skills-to-job mismatches—which are conceptually intertwined but have rarely been theoretically and empirically integrated.

These two strands of research are theoretically compatible because both are fundamentally concerned with workers' skill endowments and job skill requirements. Research on technological change has long argued that digital technologies transform workplace skill requirements, task structures, and the demand for skills. At the same time, the skills mismatch literature focuses on the congruence between workers' skill endowments and the skills required for their jobs. Technological change can therefore be understood as an important mechanism through which job skill requirements are reshaped, potentially generating new forms of underskilling and overskilling. From this perspective, analysing digitalisation through the lens of skills mismatch provides a theoretically coherent framework for understanding how technological transformation affects the relationship between workers and jobs.

The economic literature on the effects of technological change has predominantly conceptualised skill demands or requirements through job tasks, often drawing on the task-based approach (Autor et al. 2003), which understands jobs as bundles of tasks and examines how technological change reshapes job content (Spitz-Oener 2006). While the contributions of this task-based approach are important—particularly in enabling the analysis of task changes at the worker level and avoiding inferences based solely on occupational structure (Green 2012)—it remains focused on the demand side of the mismatch equation, that is, job requirements. It is less well suited to capture the temporary or persistent mismatches between demand and supply of skills.

A conceptualisation of skills mismatch, which includes both skill surpluses (overskilling) and deficits (underskilling), must also incorporate the supply side: the skill endowments that workers bring to their jobs. In addition, the skills-mismatch approach conceptually distinguishes between tasks and skills. While tasks refer to units of work activity that produces output, skills represent a workers' endowment of capabilities for performing various tasks (Acemoglu and Autor 2011, p. 1045). The International Labour Organization (ILO International Labour Office 2012), through the International Standard Classification of Occupations (ISCO-08), makes a similar distinction: a job is defined as a set of tasks and duties performed—or intended to be performed—by one person, while skills are the abilities to carry out those tasks and duties (ILO International Labour Office 2012). Therefore, tasks are characteristics of jobs, whereas skill endowments are characteristics of workers (Autor and Handel 2013).

Previous research on the consequences of digital technologies has shown a tension between beneficial and unfavourable effects on job quality (Andries et al. 2002; Chesley 2014; Wegman et al. 2018; Kortmann et al. 2022). Digitalisation processes may reduce the monotony of activities or physical strain, improve employment security (Bisht et al. 2023) or enhance autonomy (Felstead and Henseke 2017; Felstead et al. 2019). However, digital technologies can increase the intensity and quantity of

work as well as the complexity and diversity of tasks (Baccini and Cioni 2010; Marler and Liang 2012). For some specific technologies such as artificial intelligence, scholars have even suggested that the final outcomes depend on the way technology is implemented in the workplace, as it may augment skills by increasing complexity and learning or it may reduce workers' autonomy (Holm and Lorenz 2022). Therefore, technology enhances opportunities for learning at work while simultaneously requiring additional knowledge and different skills (Demerouti 2022).

The common support for the idea that digital technologies impact jobs' skill requirements (Green et al. 2003) has made for an increasing debate on the need for further training and a growing body of research demonstrating the importance of lifelong learning and training for workers (Desjardins and Rubenson 2011, 2013; Konings and Vanormelingen 2015; Webb et al. 2022; Brandi et al. 2023). While initial schooling is foundational for skill endowments, skills continue to develop through formal and informal learning, the last taking place at the workplace outside formal educational settings. Learning by doing and learning from supervisors and co-workers are all crucial mechanisms of on-the-job learning (Jarosch et al. 2021; De Grip et al. 2016). Recent research points to on-the-job learning as a more relevant factor for workers' human capital development than formal training (De Grip 2024) and the most prevalent form of on-the-job learning (Cerasoli et al. 2018). Nevertheless, skills mismatches have remained peripheral to this debate.

Skills mismatches occur when the overall level of workers' skill endowments is above (i.e. overskilling) or below (i.e. underskilling) the overall level of skills required for their job. Both sides of skills mismatches have been analysed in previous studies (Flisi et al. 2017; McGuinness et al. 2018). In the few studies analysing mismatches within the discourse of digitalisation and technological change, underskilling has monopolised the discourse, probably due to the expected increase in job skill requirements and the narrative of required upskilling of the workforce (Schlogl et al. 2021). Some studies expect an increase in underskilling if workers and training systems are not capable of updating and meeting the changing skill requirements (Allen and van der Velden 2002; Fregin et al. 2020).

In contrast, previous research has clearly fallen short in analysing overskilling within the context of digitalisation—a shortcoming that this study intends to solve. Overskilling means that workers' existing skills are underutilised in jobs that require lower skills. Overskilling is associated with overall negative consequences for workers and labour markets, as available skills are not put to the right use (Allen et al. 2013; Perry et al. 2014; Santiago-Vela and Hall 2023). Overskilling is detrimental (Sloane and Mavromaras 2020), particularly considering the decisive role in workers' skill development of learning from tasks performed on the job and work-related learning (Ferreira et al. 2017; De Grip 2024). Opportunities for development and learning at work have been considered an important job resource (Bakker and Demerouti 2017). Skills used at work can be considered as an intrinsic aspect of job quality that is positively affected by computerisation (Felstead et al. 2019). An additional shortcoming of previous studies has

been the lack of focus on the workplace. Using occupational databases such as O*NET goes along with a limiting assumption that employees and workplaces covered by the same occupational category are identical in terms of tasks and skills (Lloyd and Payne 2019; Holm and Lorenz 2022), which hinders analyses on skill changes within jobs. While acknowledging the efforts of previous prominent studies that relied on skill measurements at the level of occupations (Liu and Grusky 2013), we argue that workplaces are the natural level of analysis for jobs that are transformed but not eliminated by the introduction of digital technologies.

Our research question is mainly informed by the effective skill model (Van der Velden and Bijlsma 2019), as well as by practice engagement theory, self-efficacy theory, social exchange theory, and the “use-it-or-lose-it” hypothesis, which all suggest that skills are not static attributes but can be shaped (growing or deteriorating) by their use. First, following the effective skill model, productivity depends on the interaction between workers' skill endowments and the extent to which these endowments are activated at the job. Accordingly, skill endowments affect income only when they are put to productive use. Second, according to practice engagement theory (Reder 1994), engaging in demanding activities contributes to skill development during adulthood. Reder et al. (2020) provide empirical support for this practice engagement theory in Germany, showing that sustained engagement with complex literacy and numeracy practices is positively associated with increases in workers' skill endowments. Third, self-efficacy theory (Bandura 1977) further suggests that individuals who believe in their own capabilities are more likely to take on new and demanding activities, thereby facilitating continued skill development. Fourth, drawing on social exchange theory (Blau 1964), we argue that skill surpluses may be perceived by workers as a breach in the psychological contract leading to disengagement, as overskilled workers feel that their investments in skill acquisition are not reciprocated by opportunities for use.

Fifth, the “use-it-or-lose-it” mechanism illustrates how underused skills may erode over time due to lacking opportunities to skill use at job (De Grip et al. 2008). Thus, one would expect overskilled workers to be more vulnerable to experience skill decline because their skills are not activated in the workplace (De Grip and van Loo 2002). Conversely, underskilled workers would develop the necessary skills when exposed to demanding and supportive work environments, leading to what has been considered in previous work as jobs with greater intellectual challenge (De Grip et al. 2008; Santiago-Vela and Hall 2023). As such, it is fair to recognise that underskilling can often be a transitional state, especially in technologically dynamic settings, given that engagement in challenging tasks may foster skills. Accordingly, the present study treats underskilling as a potential snapshot within an ongoing process of skill adaptation, rather than as a necessarily permanent or undesirable condition. In this sense, recent European comparative research finds that digitalisation—despite its potential to devalue certain existing skills—also facilitates dynamic upskilling by increasing task variety, job complexity, and training opportunities (McGuinness et al. 2023).

After considering the points raised in the above discussion, we formulate several hypotheses:

2.1 | Impact of Digital Technologies on Skills Mismatches

As it is assumed that digitalisation increases skill requirements, it should be positively related to a lack of workers' skills and negatively related to the underutilisation of available skills.

The introduction of digital technologies in the workplace leads to a higher probability of underskilling (H1).

The introduction of digital technologies in the workplace leads to a lower probability of overskilling (H2).

2.2 | Effect Heterogeneity by Company's Level of Digital Technologies

Early in the debate on labour market inequalities, proponents of labour market segmentation theories suggested that the labour market is divided into various enduring segments, each governed by its own specific regulations and conditions (Doeringer and Piore 1971; Sengenberger 1981; Lindbeck and Snower 1986). This principle of labour submarkets has accompanied a long sociological tradition in acknowledging the heterogeneity across sectors and companies characterised by different skill requirements. For a thorough discussion of digitalisation, it appears theoretically sound to also consider—beyond the microlevel of workplaces and workers—the meso-level of companies.

It is suggested that the adoption of technology is embedded in organisational contexts, with companies (and their aggregation in economic sectors) exhibiting heterogeneous technology intensity and application in work processes (Ohlert et al. 2022). Digitalisation has permeated every sector, yet notable variations remain evident (Arntz et al. 2016). Under the lens of the task-based approach, less digitally mature sectors are considered more prone to automation than more digitally mature ones, primarily due to their high numbers of workers with manual tasks (Frey and Osborne 2017). Important empirical evidence from Germany has also shown that digitalisation is particularly beneficial for low and middle-skilled workers (Genz et al. 2019).

Extrapolating these insights to the debate on skills-to-job mismatches, it can be expected that digitalisation dynamics will be most pronounced in sectors in which digital technologies have been more strongly implemented; in more digitally mature sectors and companies, technology adoptions are common practice. Therefore, as existing technology can be seen as an important precondition of new technology (Howcroft and Taylor 2023), we expect the impact of new digital technologies on skills mismatches to depend on the extent of companies' technology adoption.

The higher the level of technology in companies, the weaker the effect of introducing digital technologies on increasing the probability of underskilling (H3).

Moreover, the beneficial impact of digital technologies in avoiding an underutilisation of skills at work (i.e. the negative relationship between digital technologies and overskilling) may be weaker for those working at more digitally matured sectors in which high-skilled jobs (i.e. jobs requiring high skills) are

more common. Sectors with lower levels of digital technologies entail fewer complex jobs that do not require high skills. Particularly in such less digitally matured contexts with low-skilled jobs, the introduction of new technologies can make a difference in increasing job complexity, avoiding underutilising existing skills.

The higher the level of technology in companies, the weaker the effect of introducing digital technologies on reducing the probability of overskilling (H4).

3 | Data, Variables and Methods

3.1 | Data and Sample

This study uses two datasets to integrate the meso and the micro-level of companies and workers. First, we use microdata from the BIBB/BAuA Employment Survey 2018 (Hall et al. 2020), a probability-based sample of persons in active employment in Germany with at least of 10 working hours per week, excluding apprentices. The dataset contains the necessary information to measure digital technologies at the workplace and individual skills-to-job mismatches, as well as other important workplace and socio-demographic characteristics of workers.

Second, we draw on information from the BIBB Training Panel—An Establishment Panel on Training and Competence Development 2018 (BIBB Training Panel 2018) (Gerhards et al. 2022), a repeating survey of establishments in Germany that has been conducted annually since 2011. We link the level of digital technologies in establishments (aggregated to economic sectors) to the BIBB/BAuA Employment Survey 2018.

The final dataset allows us to control for workplace and workers heterogeneity within the same occupational title. An additional strength lies in the measurement of digitalisation, which is directly assessed by the introduction of digital technologies in the workplace and the existing level of digital technologies in companies. This is instead of the approach of approximating digitalisation with the substitution potential of occupations, commonly used in previous studies (Frey and Osborne 2017). The analytical sample was restricted to employees up to the age of 65 and used a total of 15,867 employees with complete information on all variables.

3.2 | Variables

3.2.1 | Skills (Mis-)Matches

The *dependent variable* refers to skills-to-job mismatches, operationalised using a self-report approach. Skills mismatch is typically measured either (1) directly, using self-reported assessments of mismatch, or (2) indirectly, by identifying jobs' skill requirements and workers' skill levels separately (Perry et al. 2014). When following the second approach, it is common to rely on general skill measures (such as literacy or numeracy) or on self-reported information about skill requirements (such as tasks performed at work) to apply either the job requirement approach (JRA) or the realised match approach (RM; see Allen et al. 2013; Pellizzari and Fichen 2017).¹

Self-reported skills mismatches are widely used in the mismatch literature (Allen 2001; Green and McIntosh 2007; Mavromaras et al. 2009). While potentially prone to reporting bias (Capsada-Munsech 2019), they offer key advantages. First, they capture job-level requirements without relying on aggregated occupational data (e.g. for education mismatch, Hartog 2000; McGuinness 2006; Leuven and Oosterbeek 2011). Second, they measure general rather than domain-specific mismatches (Pérez Rodríguez et al. 2024). Third, they flexibly reflect evolving job demands over time (Capsada-Munsech 2019), aligning with findings that workers are well placed to assess their job content (Storm 2023). Especially in contexts of technological change, they provide a timely and less biased measure.

This study relies on workers' self-reported mismatch by using the following question: "If you now compare the requirements in your job with your current occupational knowledge and skills, what would you say?", with three possible responses: "the requirements correspond to my occupational knowledge and skills," "the requirements are higher" and "the requirements are lower." The final variable for skills mismatches contains the following three categories: (1) skills match, (2) underskilled, (3) overskilled. The same self-assessed measure has already been applied in previous mismatch studies (Rohrbach-Schmidt and Tiemann 2016; Santiago-Vela and Hall 2023). Importantly, it has two notable strengths in reducing reporting bias. First, it is phrased in a neutral way and avoids direct statements such as "being underskilled," which may appear judgemental to respondents (McGuinness et al. 2018). Second, the question is intentionally restricted to job-related requirements (i.e., 'compare the requirements in your job with your current occupational knowledge and skills'), rather than covering all skills possessed by workers that may be applicable outside the job context.

At the same time, this measure captures workers' subjective assessments of the relationship between their skills and job requirements. Workers may still include skills that they possess but which are not directly required for their jobs. This could lead to an overestimation of overskilling and an underestimation of underskilling. However, alternative measures based on occupational averages of general skills or task proxies may also struggle to capture job-specific requirements and within-occupation heterogeneity, which could also lead to an underestimation of underskilling. Therefore, while not immune to reporting bias, the self-assessed measure employed here can be a reasonable option for analysing mismatch at the workplace level in the context of technological change.

3.2.2 | Introduction of Digital Technologies in the Workplace

The *explanatory variable* measures the introduction of digital technologies in the workplace by asking whether new computer programmes have been introduced in the immediate working environment of workers in the last 2 years (response options: yes or no). This variable contains a dynamic component that captures the adoption of technology in the workplace over a 2-year period. Moreover, it contributes to the scarce evidence that relies on direct items on technological change, rather than the more common approach of automation risks (Frey and Osborne 2017; Nedelkoska and Quintini 2018) or indicators

derived from expert assessments that ignore workplace heterogeneity (Storm 2023).

Alternative approaches have measured the diffusion of industrial robots to analyse wages and employment (Acemoglu and Restrepo 2020; Dauth et al. 2017). However, using industrial robots as the sole measure of digitalisation limits the validity of extrapolating results across all labour market sectors; robots are mainly used in manufacturing, while digitalisation is also crucial in other economic sectors, such as services (Genz et al. 2019). Other scholars have opted for a more inclusive approach based on digital technologies to assess the impact of digitalisation in all economic sectors (Genz et al. 2019; Falck et al. 2024). While it is appropriate to acknowledge that computer-based technologies may be driven by different impulses in different companies and sectors (Ohlert et al. 2022), the present analysis covers all economic sectors and therefore focuses on less sector-specific computer-based technologies—those that can be generalised and applied to all different work contexts.

New computer programmes are directly intertwined with computers and internet use, which continues to be a pivotal measure in prominent analyses on technological change (Akerman et al. 2015; Arntz et al. 2025). Therefore, while new computer programmes do not encompass all new digital technologies, they encircle the adoption of digital technologies that are expected to substantially alter the requirements on knowledge and skills, promoting the use of higher cognitive skills (Green 2012).

3.2.3 | Level of Digital Technologies

While the explanatory variable already measures the adoption of digital technologies, the existing *level* of digitalisation is equally important to capture the extent to which digital technologies are used and how familiar workers are with digitalised work environments. To gather this additional information, we relied on information on the use of 14 different categories of digital technologies in the field of information technology collected in the BIBB Training Panel 2018. The specific digital technology items, which have already been used in previous research to contextualise technological change (Lammers et al. 2023), are summarised in Table A1 in the Appendix. We then summed up the digital technologies used in each company to generate an indicator of the level of digital technologies used by each company.² We aggregated this indicator by calculating weighted averages at the level of economic sectors (NACE). Our final index captures sector-specific averages of the different levels of digital technology use in companies. We assume that workers in a digitally mature sector are also, on average, subject to large use of digital technologies at their particular company.

Figure 1 shows which economic sectors have higher levels of digital technology. Companies engaged in the manufacture of computers, electronic and optical products, chemicals and pharmaceuticals, as well as in the fabrication of metal products and machinery, are among the most intensive users of digital technologies. Conversely, as illustrated in Figure 2, sectors such as education and teaching have below-average levels of digital technology use, while companies in other sectors such as accommodation and gastronomy or administration and management of companies are characterised by

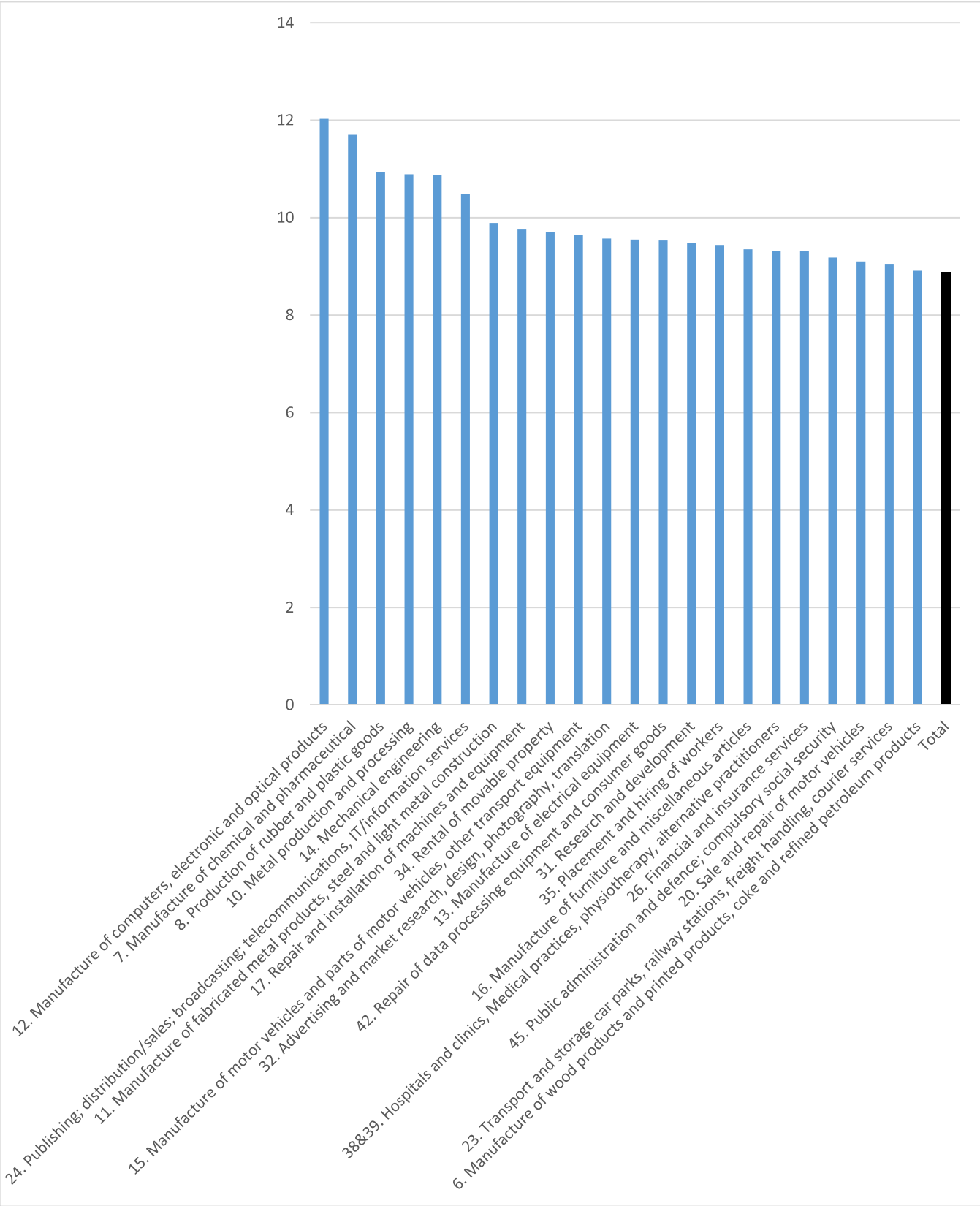


FIGURE 1 | Level of digital technology use across economic sectors (above-average levels). *Source:* BIBB Training Panel 2018. Author's calculations. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/nwpe.70036)]

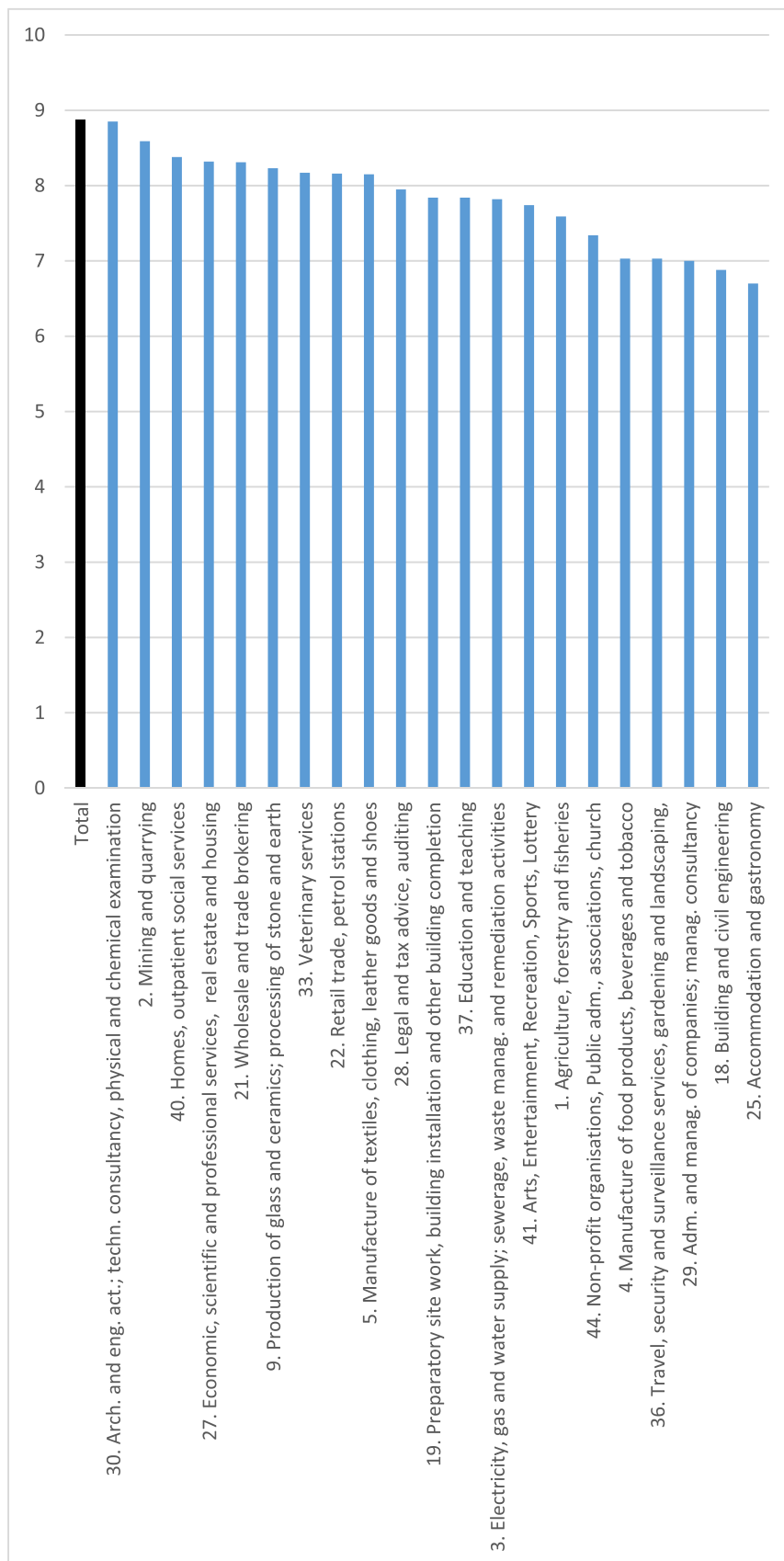


FIGURE 2 | Level of digital technology use across economic sectors (below-average levels). *Source:* BIBB Training Panel 2018. Author's calculations. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/nwpe.70035)]

TABLE 1 | Distribution of variables across samples.

	Mean			Differences (<i>t</i> -test)
	Total	With intro. tech.	Without intro. tech.	
Introduction of new technologies (computer programmes)	0.45			
Level of digital technologies	8.84	9.04	8.67	−0.370***
Skills (mis-)match				
Skills match	0.57	0.58	0.56	−0.010
Overskilled	0.18	0.14	0.21	0.064***
Underskilled	0.25	0.28	0.23	−0.053***
Women (vs. men)	0.47	0.44	0.49	0.062***
Migration background (vs. no migration background)	0.18	0.19	0.18	0.003
Tenure (years)	11.95	13.71	10.49	−3.426***
Further training participation (vs. no participation)	0.61	0.70	0.54	−0.140***
Education level				
No formal qualifications	0.08	0.06	0.09	0.021***
VET	0.65	0.63	0.67	0.063***
Academic level	0.27	0.31	0.24	−0.084***
Job requirement level				
Unskilled tasks	0.07	0.05	0.09	0.030***
Skilled tasks	0.55	0.50	0.59	0.094***
Complex tasks	0.17	0.20	0.15	−0.059***
Highly complex tasks	0.21	0.25	0.18	−0.065***
Occupations				
Raw materials extraction occupations	0.01	0.01	0.02	0.009***
Occupations in machining, processing and repairing	0.11	0.09	0.13	0.036***
Occupations in machinery and equipment control and maintenance	0.06	0.07	0.06	0.001
Goods trade and distribution	0.10	0.10	0.10	0.001
Traffic, storage, transportation, security	0.10	0.09	0.12	0.021***
Catering and cleaning occupations	0.06	0.03	0.08	0.037***
Office and commercial service occupations	0.14	0.17	0.12	−0.049***
Technical and scientific occupations	0.12	0.17	0.08	−0.097***
Legal, management and business occupations	0.05	0.06	0.04	−0.026***
Arts, media, humanities and social science occupations	0.03	0.03	0.03	−0.005
Health and social occupations, care	0.15	0.13	0.16	0.057***
Teaching occupations	0.06	0.05	0.06	0.016***
Sectors				
1. Agriculture, forestry and fisheries	0.01	0.01	0.01	0.005***
2. Mining and quarrying	0.00	0.00	0.00	−0.001
3. Electricity, gas and water supply and utilities	0.02	0.02	0.02	−0.007**
4. Manufacture of food products, beverages and tobacco	0.02	0.02	0.02	0.008***
5. Manufacture of textiles, clothing, leather goods and shoes	0.01	0.01	0.01	0.001
6. Manufacture of wood products, paper and paperboard and refined petroleum products	0.01	0.01	0.01	0.001

(Continues)

TABLE 1 | (Continued)

	Mean			Differences (<i>t</i> -test)
	Total	With intro. tech.	Without intro. tech.	
7. Manufacture of chemical and pharmaceutical products	0.03	0.04	0.04	−0.019***
8. Production of rubber and plastic goods	0.01	0.01	0.01	−0.000
9. Production of glass and ceramics; processing of stone and earth	0.01	0.01	0.01	−0.002*
10. Metal production and processing	0.01	0.01	0.01	−0.000
11. Manufacture of fabricated metal products, steel and light metal construction	0.04	0.04	0.04	0.000
12. Manufacture of computers, electronics and optical products	0.01	0.01	0.01	−0.006***
13. Manufacture of electrical equipment	0.03	0.04	0.04	−0.010***
14. Mechanical engineering	0.03	0.03	0.03	−0.002
15. Manufacture of motor vehicles and parts of motor vehicles, other transport equipment	0.06	0.07	0.07	−0.026***
16. Manufacture of furniture and miscellaneous articles	0.01	0.01	0.01	−0.002
17. Repair and installation of machines and equipment	0.00	0.00	0.00	−0.001
18. Building and civil engineering	0.02	0.01	0.01	0.007***
19. Preparatory site work, building installation and others	0.03	0.02	0.02	0.018***
20. Sale and repair of motor vehicles	0.01	0.01	0.01	−0.002
21. Wholesale and trade brokering	0.01	0.01	0.01	0.002
22. Retail trade, petrol stations	0.07	0.06	0.06	0.013***
23. Transport and storage car parks, railway stations, couriers etc.	0.05	0.05	0.05	0.012***
24. Publishing; distribution/sales; ITC services	0.04	0.06	0.06	−0.043***
25. Accommodation and gastronomy	0.03	0.02	0.02	0.014***
26. Financial and insurance services	0.03	0.05	0.05	−0.029***
27. Economic, scientific and professional services, property	0.01	0.00	0.00	0.000
28. Legal and tax advice, auditing	0.01	0.01	0.01	0.002
29. Admin. and management of companies; Management consultancy	0.00	0.00	0.00	−0.002*
30. Architectural and engineering activities; technical consultancy	0.01	0.01	0.01	−0.004*
31. Research and development	0.01	0.01	0.01	−0.001
32. Advertising and market research, design, translation	0.01	0.01	0.01	0.000
33. Veterinary services	0.00	0.00	0.00	0.001*
34. Rental of movable property	0.00	0.00	0.00	0.000
35. Placement and hiring of workers	0.00	0.00	0.00	0.000
36. Travel, security services, gardening and landscaping	0.03	0.02	0.02	0.016***
37. Education and teaching	0.08	0.06	0.06	0.036***
38 & 39. Hospitals and clinics, Medical practices, physiotherapy, alternative practitioners	0.09	0.08	0.08	0.017***

(Continues)

TABLE 1 | (Continued)

	Mean			Differences (t-test)
	Total	With intro. tech.	Without intro. tech.	
40. Homes, outpatient social services	0.06	0.05	0.05	0.028***
41. Arts, Entertainment, Recreation, Sports, Lottery	0.01	0.01	0.01	0.006***
42. Repair of data processing equipment and consumer goods	0.00	0.00	0.00	−0.000
43. Other mainly personal services (e.g. laundry, hairdresser)	0.01	0.00	0.00	0.002*
44. Non-profit organisations, associations, churches	0.01	0.01	0.01	0.003
45. Public administration and defence, compulsory social security	0.08	0.10	0.10	−0.036***
Company location (Bundesland)				
Schleswig-Holstein	0.03	0.03	0.03	0.003
Hamburg	0.03	0.03	0.03	−0.004
Lower Saxony	0.09	0.09	0.09	0.003
Bremen	0.01	0.01	0.01	0.002
North Rhine-Westphalia	0.20	0.20	0.21	0.002
Hessen	0.08	0.09	0.07	−0.018***
Rhineland-Palatinate	0.04	0.04	0.04	0.000
Baden-Wuerttemberg	0.14	0.15	0.14	−0.007
Bavaria	0.17	0.18	0.16	−0.023***
Saarland	0.01	0.01	0.01	0.000
Berlin	0.05	0.05	0.05	0.008*
Brandenburg	0.03	0.03	0.03	0.004
Mecklenburg-Western Pomerania	0.02	0.02	0.02	0.007***
Saxony	0.05	0.04	0.05	0.011**
Saxony-Anhalt	0.02	0.02	0.03	0.010***
Thuringia	0.02	0.02	0.03	0.002

Note: Mean values. Sample distributions (total sample, sample with and sample without introduction of computer programmes) and sample differences (t-tests).

Significance levels: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Sample includes workers aged 18–65 years.

Source: BIBB/BAuA Employment Survey 2018 and BIBB Training Panel 2018. Author's calculations.

the lowest levels of digital technology use. Figure A1 in the Appendix also shows the frequencies of the 14 different digital technologies used in the sample. Non-portable IT and network technologies are the most commonly used digital tools, while technologies that operate relatively autonomously such as smart factories and Internet of Things are more scarcely used.

3.2.4 | Control Variables

Our analyses control for a range of confounders that influence the relationship between the adoption of new computer programmes and skills mismatches. These include educational attainment (given that technology is expected to be used more productively by better educated workers) (Goos and Manning 2007), participation in further training during the last 2 years (as an instrument for updating skills in the course of digitalisation) (Brunello and Wruuck 2021; Kortmann et al. 2023), requirement level of the job, tenure, gender and migration background, current occupation, economic sector and location of the company measured at the *Bundesland* level, i.e., region.

3.3 | Descriptive Statistics

The distribution of all variables included in Table 1 indicates that fewer than half of the workers have jobs at workplaces where new computer programmes were introduced within the last 2 years. Regarding the dependent variable of skills-to-job mismatches, 25 percent of the total sample of workers demonstrated an underutilisation of their skills through overskilling, while 18 percent exhibited lower skills than those required for their workplaces (underskilling). Furthermore, a clear distinction emerges when the total analytical sample is divided into two groups: workers whose workplaces have introduced new computer programmes and those whose workplaces have not. Workers in workplaces with technology adoption are significantly less likely to be overskilled (14 vs. 21 percent) and significantly more likely to be underskilled (28 vs. 23 percent) compared to those in workplaces without such adoption. This is consistent with the argument put forth in this study that new digital technologies lead to the emergence of new, higher skill requirements, which in turn can result in situations of underskilling or skill shortages.

Moreover, a more detailed examination of the mean differences reveals systematic variation in the remaining control variables between groups of workers. Workers whose workplaces have adopted technologies are more often male, more experienced in their companies, participate more often in further training, attained higher education levels and perform more complex tasks. These results have important repercussions for the causal modelling of technology and skills-to-job mismatches because they raise concerns about the exogeneity of our independent variable technology adoption, which would lead to biased results if not accounted for. The following section focuses on the estimation strategy used to tackle these significant differences across workers.

3.4 | Estimation Strategy

Given the results on descriptive statistics, the exogeneity assumption of our independent variable technology adoption necessary for causal claims is likely to not be fulfilled. Workers in workplaces with high requirement levels (which are therefore more apt to underskill) differ systematically from workers in workplaces with low requirement levels (which are therefore more apt to overskill), and these individual differences are also likely to relate to the adoption of digital technologies in the workplace. To account for this potential endogeneity of the introduction of computer programmes, this study employs an entropy balancing method (Hainmueller 2012; Hainmueller and Xu 2013) to create a control group of workers whose workplaces have not introduced computer programmes. Entropy balancing is a re-weighting technique designed to adjust for confounding in observational studies, aiming to approximate the conditions of a randomised controlled trial. This method achieves balance across treatment and control groups (e.g. workers in workplaces with and without the introduction of new computer programmes) by solving a constrained optimisation problem that adjusts sample weights to equalise the distribution of pre-specified covariate moments (e.g. means, variances).

Unlike traditional matching or weighting methods, entropy balancing allows for precise specification of balance objectives without relying on a specific outcome model. By directly minimising an entropy-like measure subject to covariate balancing constraints, it efficiently mitigates endogeneity bias in causal inference analyses. This suggests that any remaining differences in the outcomes of skills mismatches between the two groups of workers can be attributed to the introduction of new computer programmes in their workplaces. Despite its advantages in handling observed confounders and enhancing estimation efficiency, entropy balancing cannot adjust for unobserved confounders and assumes correct specification of relevant covariates for balance.

The models for entropy balancing consider all the control variables as covariates in the regular analyses (see Table 1) and two additional variables: age group of workers and company size.

To evaluate the balancing of the covariates included in the entropy balancing method, as suggested by Hainmueller (2012) and Hainmueller and Xu (2013), we consider two indicators (see

Table 2). The first is a *t*-test for mean equality between treatment and control group (Caliendo and Kopeinig 2008). The second is the normalised differences between the treatment and the control group (Rosenbaum and Rubin 1985).

From the results of the two tests of covariate balance shown in Table 2, it is safe to declare a successful balance of all the covariates considered. The *t*-tests indicate that the treatment and control groups are equal, while the normalised mean differences are far from exceeding the critical value of 5 usually considered in the relevant literature (Caliendo and Kopeinig 2008). This equality holds for all covariates, including control variables such as educational attainment, participation in further training or job requirements and the two additional variables of age and company size.

Finally, we used the generated entropy balancing weights to compute multinomial logistic regression models on the categorical dependent variable of skills-to-job mismatch. To interpret and compare the regression coefficients of the effects of technology adoption, we computed average marginal effects (AME) (Mood 2010). To test the hypothesis of potential effect heterogeneity by level of digital technology, we interacted the dependent variable with the level of digital technology and graphically illustrated the findings on predicted probabilities (Mize 2019).

4 | Results

4.1 | Main Effects of Technology on Skills Mismatches

Table 3 illustrates the main results (AME) from multinomial logistic regression of technology adoption on skills-to-job mismatches. Regarding the effect on underskilling, the results confirm that the introduction of new computer programmes in the workplace is associated with a 3.8 percentage-point higher probability of workers being underskilled (H1). This is plausible given that technology adoption may induce an increase in the knowledge and skill requirements required at work. This makes it more likely that skill requirements overpass the skill endowments of workers, leading to underskilling or skills shortages. The predicted probabilities (not shown in Table 3) suggest that, on average, 24.7 percent of workers who have not been introduced to digital technologies over the past 2 years are underskilled, while in the group of workers who have experienced the adaptation of digital technologies, 28.5 percent are underskilled.

The results in Table 3 also indicate that workers in workplaces that have undergone the introduction of new computer programmes have a 2.5 percentage-point lower probability of being overskilled. This provides support for H2. Arguably, the underutilisation of skills in the workplace is undesirable. Consequently, the adoption of technology in the workplace can be regarded as a beneficial factor in preventing this unfavourable outcome.

4.2 | Heterogeneous Effects of Technology on Skills Mismatches

We expected more digitally mature sectors to offer different contexts for skill adaptation in response to the technology-driven changes in skill requirements compared to less digitally

TABLE 2 | Comparisons of covariate means in workplaces with and without introduction of computer programmes, after entropy balancing matching.

	Mean Control (without intro. tech.)	Mean Treatment (with intro. tech.)	Diff.	t-test (p-value)	Std. differences (in %)
Women (vs. men)	0.47844	0.47849	0.0	−0.01	0.996
Migration background (vs. no migration background)	0.09949	0.09951	0.0	0.00	0.997
Tenure (years)	15.526	15.523	0.0	0.02	0.987
Further training participation (vs. no participation)	0.72857	0.72838	0.0	0.03	0.979
Education level					
No formal qualification	0.03648	0.03653	0.00	−0.02	0.986
VET	0.54503	0.54512	0.00	−0.01	0.99
Academic level	0.41849	0.41835	0.00	0.02	0.985
Job requirement level					
Unskilled tasks	0.03112	0.03122	0.00	−0.03	0.972
Skilled tasks	0.42015	0.42024	0.00	−0.01	0.991
Complex tasks	0.22997	0.22991	0.00	0.01	0.992
Highly complex tasks	0.31875	0.31863	0.00	0.02	0.987
Occupations					
Raw materials extraction occupations	0.00485	0.00489	0.00	−0.04	0.97
Occupations in machining, processing and repairing	0.05918	0.05923	0.00	−0.01	0.989
Occupations in machinery and equipment control and maintenance	0.04018	0.04017	0.00	0.00	0.997
Goods trade, distribution	0.09031	0.09028	0.00	0.01	0.996
Traffic, storage, transportation, security	0.06952	0.06951	0.00	0.00	0.999
Catering and cleaning occupations	0.01849	0.01868	−0.10	−0.08	0.933
Office and commercial service occupations	0.19987	0.1998	0.00	0.01	0.991
Technical and scientific occupations	0.18776	0.18767	0.00	0.01	0.989
Legal, management and business occupations	0.08227	0.08224	0.00	0.01	0.994
Arts, media, humanities and social science occupations	0.03635	0.03634	0.00	0.00	0.997
Health and social occupations, care	0.12946	0.12947	0.00	0.00	0.999
Teaching occupations	0.08176	0.08173	0.00	0.01	0.994
Sectors					
1. Agriculture, forestry and fisheries	0.00485	0.00486	0.00	−0.02	0.988
2. Mining and quarrying	0.00128	0.00128	0.00	0.00	1
3. Electricity, gas and water supply, etc.	0.02207	0.02206	0.00	0.00	0.999
4. Manufacture of food products, beverages and tobacco	0.01403	0.01404	0.00	0.00	0.997

(Continues)

TABLE 2 | (Continued)

	Mean Control (without intro. tech.)	Mean Treatment (with intro. tech.)	Diff.	t-test (p-value)	Std. differences (in %)
5. Manufacture of textiles, clothing, leather goods and shoes	0.00395	0.00395	0.00	0.00	1
6. Manufacture of wood products, paper and paperboard, refined petroleum products	0.00969	0.00969	0.00	0.00	0.999
7. Manufacture of chemical and pharmaceutical products	0.03827	0.03825	0.00	0.00	0.996
8. Production of rubber and plastic goods	0.00434	0.00434	0.00	0.00	0.999
9. Production of glass and ceramics; processing of stone and earth	0.00434	0.00433	0.00	0.00	0.999
10. Metal production and processing	0.0051	0.0051	0.00	0.00	0.999
11. Manufacture of fabricated metal products, steel and light metal construction	0.02589	0.02589	0.00	0.00	0.998
12. Manufacture of computers, electronic and optical products	0.0111	0.01109	0.00	0.00	0.998
13. Manufacture of electrical equipment	0.03406	0.03404	0.00	0.00	0.997
14. Mechanical engineering	0.02793	0.02792	0.00	0.00	0.997
15. Manufacture of motor vehicles and parts of motor vehicles, other transport equipment	0.06135	0.06133	0.00	0.01	0.994
16. Manufacture of furniture and miscellaneous articles	0.01199	0.01199	0.00	0.00	0.998
17. Repair and installation of machines and equipment	0.00293	0.00293	0.00	0.00	0.999
18. Building and civil engineering	0.0111	0.0111	0.00	0.00	0.997
19. Preparatory site work, building installation and others	0.01237	0.01242	0.00	−0.03	0.976
20. Sale and repair of motor vehicles	0.00918	0.00918	0.00	0.00	0.998
21. Wholesale and trade brokering	0.00829	0.00829	0.00	0.00	0.998
22. Retail trade, petrol stations	0.05077	0.05076	0.00	0.00	0.999
23. Transport and storage car parks, railway stations, courier, etc.	0.04005	0.04005	0.00	0.00	0.999
24. Publishing; distribution/sales; ITC services	0.06722	0.06719	0.00	0.01	0.994
25. Accommodation and gastronomy	0.01173	0.0118	0.00	−0.04	0.972
26. Financial and insurance services	0.0588	0.05878	0.00	0.01	0.995
27. Economic, scientific and professional services, property	0.00689	0.00689	0.00	0.00	0.999
28. Legal and tax advice, auditing	0.01276	0.01275	0.00	0.00	0.998
29. Admin. And management of companies; Management consult	0.00561	0.00561	0.00	0.00	0.998

(Continues)

TABLE 2 | (Continued)

	Mean Control (without intro. tech.)	Mean Treatment (with intro. tech.)	Diff.	t-test (p-value)	Std. differences (in %)
30. Architectural and engineering activities; technical consultancy	0.01429	0.01428	0.00	0.00	0.998
31. Research and development	0.0102	0.0102	0.00	0.00	0.998
32. Advertising and market research, design, translation	0.00599	0.00599	0.00	0.00	0.999
33. Veterinary services	0.00026	0.00027	0.00	−0.04	0.967
34. Rental of movable property	0.00089	0.00089	0.00	0.00	1
35. Placement and hiring of workers	0.00255	0.00255	0.00	0.00	1
36. Travel, security services, gardening and landscaping	0.01352	0.01359	0.00	−0.04	0.971
37. Education and teaching	0.09273	0.09272	0.00	0.00	0.999
38. Hospitals and clinics	0.08827	0.08826	0.00	0.00	0.998
39. Medical practices, physiotherapy, alternative practitioners	0.04375	0.04377	0.00	−0.01	0.995
40. Homes, outpatient social services	0.00791	0.00792	0.00	−0.01	0.995
41. Arts, Entertainment, Recreation, Sports, Lottery	0.00128	0.00128	0.00	0.00	1
42. Repair of data processing equipment and consumer goods	0.00281	0.00281	0.00	0.00	0.998
43. Other mainly personal services (e.g. laundry, hairdresser)	0.0148	0.01479	0.00	0.00	0.999
44. Non-profit organisations, associations, churches	0.12283	0.12278	0.00	0.01	0.991
45. Public administration and defence, compulsory social security	0.00485	0.00486	0.00	−0.02	0.988
Company location (Bundesland)					
Schleswig-Holstein	0.02972	0.02972	0.00	0.00	0.999
Hamburg	0.03712	0.03711	0.00	0.00	0.999
Lower Saxony	0.08878	0.08878	0.00	0.00	0.999
Bremen	0.00842	0.00842	0.00	0.00	0.999
North Rhine-Westphalia	0.18163	0.18163	0.00	0.00	0.999
Hessen	0.08316	0.08315	0.00	0.00	0.997
Rhineland-Palatinate	0.03776	0.03776	0.00	0.00	0.999
Baden-Wuerttemberg	0.12895	0.12894	0.00	0.00	0.998
Bavaria	0.21824	0.21822	0.00	0.00	0.998
Saarland	0.00995	0.00995	0.00	0.00	1
Berlin	0.05497	0.05498	0.00	0.00	0.999
Brandenburg	0.02462	0.02462	0.00	0.00	0.998
Mecklenburg-Western Pomerania	0.01339	0.0134	0.00	−0.01	0.996
Saxony	0.04273	0.04274	0.00	0.00	0.998
Saxony-Anhalt	0.01798	0.018	0.00	−0.01	0.995
Thuringia	0.02258	0.02258	0.00	0.00	0.999
Company size					
1–9 Employees	0.07449	0.07463	0.00	−0.03	0.974

(Continues)

TABLE 2 | (Continued)

	Mean Control (without intro. tech.)	Mean Treatment (with intro. tech.)	Diff.	t-test (p-value)	Std. differences (in %)
10–49 Employees	0.20689	0.20696	0.00	−0.01	0.991
50–249 Employees	0.27679	0.27674	0.00	0.01	0.994
250/more Employees	0.44184	0.44168	0.00	0.02	0.984
Age group					
15–34 years old	0.16339	0.16341	0.00	0.00	0.997
35–44 years old	0.21122	0.21121	0.00	0.00	0.998
45–54 years old	0.3324	0.33239	0.00	0.00	0.999
55–65 years old	0.29298	0.29299	0.00	0.00	0.999

Note: Sample includes workers aged 18–65 years. Entropy-balanced weighted results.

Source: BIBB/BAuA Employment Survey 2018 and BIBB Training Panel 2018. Author's calculations.

mature contexts. Figure 3 shows the results of heterogeneous effects across levels of digital technologies, illustrating the predicted probabilities of both groups (workers in workplaces with and without the introduction of new computer programmes) across the different levels of digital technologies in sectors. Solid lines for both groups indicate that the effect of technology adoption is statistically significant at conventional levels, meaning that predicted probabilities differ significantly between the groups. Otherwise, dashed lines are shown. Figure 3a shows the results for underskilling (H3). In sectors with low average levels of digital technology use across companies, we find no significant effect from introducing new computer programmes on the probability of underskilling; the probability of both groups does not significantly differ. Nevertheless, across all other levels of technology use, workers who have not been introduced to digital technologies show significantly higher probabilities of being underskilled. The positive relationship between new technologies and the probability of being underskilled applies to all workers, irrespective of the level of digital technologies. Therefore, the results do not support heterogeneity in the effects on underskilling, as stipulated by H3.

Finally, Figure 3b indicates that heterogeneous effects can be observed in overskilling (H4). Consequently, the negative relationship between the introduction of new technologies and overskilling is statistically significant in low and medium-digitalised sectors, whereas in digitally matured sectors the probability of being overskilled does not depend on the adoption of new computer programmes. This suggests that this type of technology adoption in the workplace is crucial to preventing the underutilisation of skills through overskilling, particularly in less digitally matured sectors that have not implemented a significant number of digital technologies.

4.3 | Limitations and Supplementary Analyses

By combining micro- and meso-level data for workers and companies in Germany, this study complements research based on indicators on the occupational or economic sector level (Minardi 2025) with evidence on the impact of digital technologies on skills mismatches at the more fine-grained level of

workplaces. The large number of variables allows us to control for a variety of potential results-biasing confounders that have rarely been considered together in previous studies, such as educational attainment, workplace requirement level, workers' participation in further training, occupations and economic sectors. Nevertheless, the unique dataset used in this study comes at a cost; its cross-sectional nature means that the possibility of spurious correlations in the presence of other unobserved, time-invariant confounders cannot be excluded.

To add robustness to the results, our empirical strategy followed an entropy-balanced reweighting approach. While this matching technique improves comparability between workers exposed and unexposed to digital technologies, the absence of baseline data on skills mismatch limits the strength of causal interpretation. Nevertheless, the successful balancing of all considered covariates reduces the likelihood that systematic differences between treatment and control workplace groups drive the observed patterns.

In order to reap the benefits of a skills-to-job mismatch approach, we focused deliberately on measures of workplace skill requirements and workers' skill endowments rather than on workplace tasks. Nevertheless, we also conducted two supplementary analyses based on the task composition of workers' workplaces in order to acknowledge the prominent task-based approach that is widely used in research on automation and technological change (Autor et al. 2003). We benefitted from the extensive information on workplace tasks contained in our dataset, which has been widely used in previous research (Spitz-Oener 2006). Both supplementary analyses relied on the same set of 16 workplace tasks, categorized according to how frequently workers performed them at work ('often,' 'sometimes,' or 'never').

For the first analysis, which served as a sensitivity analysis, the workplace task items were classified into five task categories following Alda (2013): routine manual tasks, routine cognitive tasks, interactive tasks, non-routine manual tasks, and non-routine cognitive tasks. Based on the relative intensity of these task categories, we identified the dominant task category within each worker's workplace and included this categorical measure

TABLE 3 | Results for the introduction of new computer programmes on skills mismatches (AME).

	Skills match	Overskilling	Underskilling
Introduction new computer programmes (vs. no introduction)	−0.013 (0.008)	−0.025*** (0.007)	0.038*** (0.008)
Level of digital technologies in sectors	0.007 (0.004)	−0.007 (0.005)	0.001 (0.003)
Women (vs. men)	−0.000 (0.010)	−0.005 (0.007)	0.006 (0.009)
Further training participation (vs. no participation)	0.020** (0.008)	−0.058*** (0.007)	0.038*** (0.007)
Tenure (years)	0.001* (0.000)	−0.003*** (0.000)	0.003*** (0.000)
Migration background (vs. no migration background)	−0.061*** (0.012)	0.036*** (0.009)	0.025* (0.013)
<i>Level of education (ref. no degree)</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
VET degree	−0.104*** (0.018)	−0.032* (0.014)	0.135*** (0.017)
University degree	−0.058** (0.022)	0.059*** (0.016)	−0.000 (0.020)
<i>Job requirement level (ref. unskilled tasks)</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Skilled tasks	0.114*** (0.018)	−0.184*** (0.019)	0.071*** (0.018)
Complex tasks	0.203*** (0.022)	−0.285*** (0.028)	0.082*** (0.022)
Highly complex tasks	0.187*** (0.023)	−0.307*** (0.026)	0.120*** (0.019)
<i>Occupations (ref. raw materials extraction occupations)</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Occupations in machining, processing and repairing	0.086 (0.086)	−0.010 (0.024)	−0.076 (0.072)
Occupations in machinery and equipment control and maintenance	0.044 (0.084)	0.011 (0.025)	−0.054 (0.069)
Goods trade, distribution	0.049 (0.081)	0.064** (0.025)	−0.113 (0.070)
Traffic, storage, transportation, security	0.072 (0.085)	0.052 (0.032)	−0.125 (0.074)
Catering and cleaning occupations	0.056 (0.091)	0.058* (0.026)	−0.114 (0.075)
Office and commercial service occupations	0.084 (0.084)	0.001 (0.022)	−0.085 (0.071)
Technical and scientific occupations	0.057 (0.086)	0.002 (0.024)	−0.059 (0.074)
Legal, management and business occupations	0.081 (0.090)	0.005 (0.023)	−0.086 (0.075)
Arts, media, humanities and social science occupations	0.056 (0.084)	0.064* (0.027)	−0.120 (0.078)
Health and social occupations, care	0.057 (0.083)	−0.028 (0.021)	−0.029 (0.070)
Teaching occupations	0.037 (0.087)	−0.010 (0.023)	−0.027 (0.073)

(Continues)

TABLE 3 | (Continued)

	Skills match	Overskilling	Underskilling
<i>Company location (ref. Schleswig-Holstein)</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Hamburg	−0.005 (0.033)	0.037* (0.016)	−0.032 (0.026)
Lower Saxony	0.001 (0.025)	−0.010 (0.015)	0.009 (0.020)
Bremen	−0.026 (0.054)	0.034 (0.041)	−0.008 (0.033)
North Rhine-Westphalia	−0.032 (0.024)	0.006 (0.015)	0.027 (0.022)
Hesse	−0.061* (0.029)	0.018 (0.016)	0.042 (0.028)
Rhineland-Palatinate	−0.004 (0.026)	−0.014 (0.018)	0.019 (0.027)
Baden-Wuerttemberg	−0.042* (0.020)	0.015 (0.014)	0.027 (0.019)
Bavaria	−0.033 (0.027)	−0.001 (0.015)	0.034 (0.026)
Saarland	−0.019 (0.045)	−0.009 (0.031)	0.028 (0.037)
Berlin	−0.063 (0.035)	0.005 (0.014)	0.058 (0.042)
Brandenburg	−0.024 (0.027)	−0.017 (0.017)	0.040 (0.032)
Mecklenburg-Western Pomerania	0.018 (0.035)	−0.017 (0.022)	−0.001 (0.027)
Saxony	−0.005 (0.044)	0.004 (0.021)	0.001 (0.035)
Saxony-Anhalt	−0.033 (0.043)	0.020 (0.023)	0.013 (0.039)
Thuringia	−0.003 (0.041)	0.005 (0.015)	−0.003 (0.043)
<i>N</i>	15,867	15,867	15,867

Note: Coefficients are AME from multinomial logit regression of the introduction of new computer programmes on skills mismatches with interaction effects between introduction of computer programmes and level of digital technologies in sectors. Entropy-balanced weighted results. Significance levels: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors in parenthesis. Sample includes workers aged 18–65 years.

Source: BIBB/BAuA Employment Survey 2018 and BIBB Training Panel 2018. Author's calculations.

as an additional control variable in the entropy-balanced regressions. Using workplace tasks as additional control variables in this manner was consistent with previous work that has interpreted workplace tasks as a mediating mechanism between computer use and job satisfaction (Minardi et al. 2023). The results remained substantively unchanged after accounting for differences in dominant task composition (see Table A2 in the Appendix).

For the second supplementary analysis, which examined heterogeneity between technology adoption and skills mismatch according to workplace routine intensity, we used the same set of 16 workplace tasks to construct two continuous indicators

(ranging from 0 to 100), which captured the relative intensity of routine and non-routine work in line with the RBTC framework. This enabled us to establish a similarity with the main heterogeneity analyses across sectoral levels of digitalisation. Routine intensity was based on routine manual and routine cognitive tasks, while non-routine intensity was based on interactive, non-routine manual, and non-routine cognitive tasks. These indicators were calculated based on the frequency with which workers performed the respective tasks. The findings are depicted graphically in Figure 4. With regard to underskilling, the results indicated that, in workplaces characterised by high levels of non-routine work (Figure 4b), the introduction of new technologies was associated with a

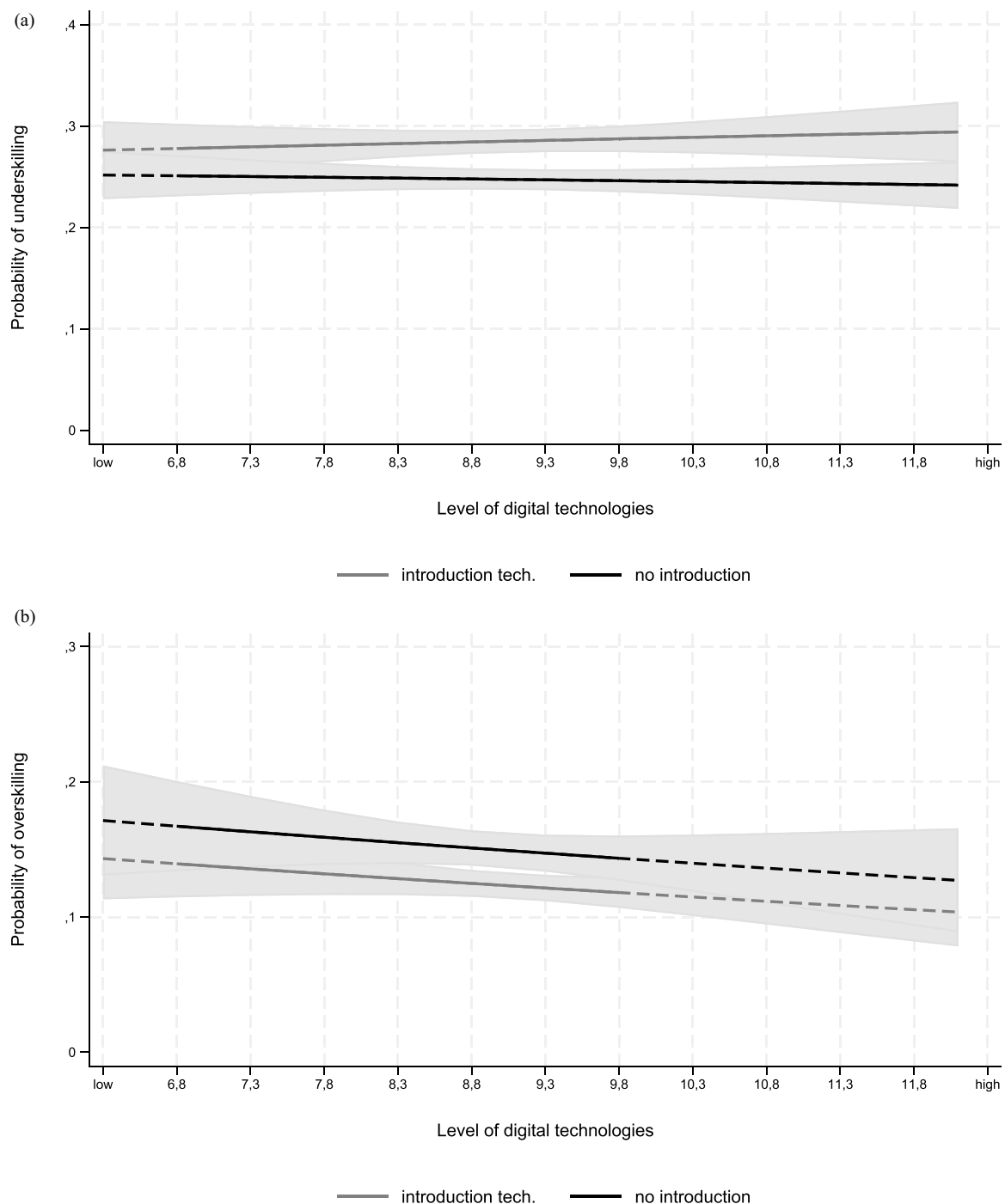


FIGURE 3 | Predicted probabilities of skills mismatch (underskilling in 3a and overskilling in 3b) for workers experiencing and not experiencing the introduction of technology (new computer programmes) across levels of digital technologies in sectors. *Notes:* Results based on a multinomial logistic model with interaction effects between introduction of new computer programmes and sector' level of digital technologies. When lines are solid (dashed), the difference between workplaces with and without introduction of new computer programmes is significant (non-significant) ($p < 0.05$). Sample includes workers aged 18–65 years. Weighted results using entropy balancing weights. *Source:* BIBB/BAuA Employment Survey 2018 and BIBB Training Panel 2018. Author's calculations.

higher probability of underskilling than in similar non-routine workplaces without technology adoption. Conversely, in workplaces characterised by high levels of routine work (Figure 4a), the probability of underskilling did not differ significantly between workplaces with and without technology adoption. However, at lower levels of routine intensity, workers in workplaces with technology adoption appeared significantly

more likely to report underskilling than comparable workers in workplaces without technology adoption. With regard to underutilisation of skills, the negative correlation between workplace digitalisation and overskilling did not appear to be confined to particular task compositions within workplaces. Overall, supplementary analyses supported the study's main findings and suggested that the relationship between workplace

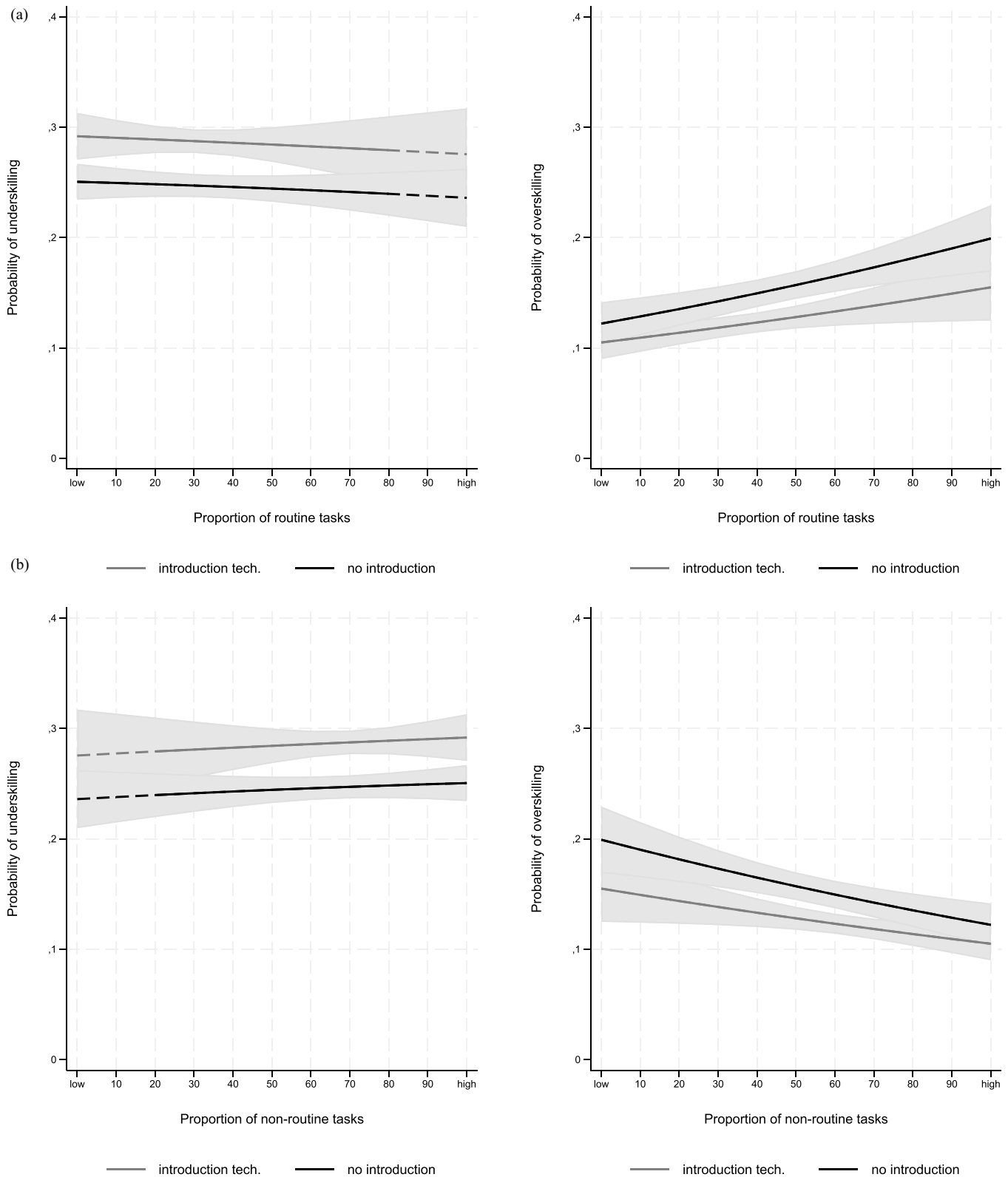


FIGURE 4 | Predicted probabilities of skills mismatch (underskilling and overskilling) for workers experiencing and not experiencing the introduction of technology (new computer programmes) across levels of routine (4a) and non-routine (4b) tasks in the workplace. *Notes:* Results based on multinomial logistic models with interaction effects between introduction of new computer programmes and level of routine and non-routine tasks. When lines are solid (dashed), the difference between workplaces with and without introduction of new computer programmes is significant (non-significant) ($p < 0.05$). Sample includes workers aged 18–65 years. Weighted results using entropy balancing weights. *Source:* BIBB/BAuA Employment Survey 2018 and BIBB Training Panel 2018. Author's calculations.

digitalisation and skills mismatches remained robust when differences in task composition were considered.

5 | Discussion

The general picture that emerges from the empirical analyses is straightforward—workplace digitalisation, as measured by the introduction of new computer programmes, is associated with a higher probability of workers being underskilled and a lower probability of their skills being underutilised due to overskilling. Furthermore, adopting new computer programmes appears important in preventing workers from underutilising their skills (particularly in less digitally mature sectors), while the positive association with underskilling seems to be similar across sectors with different levels of digital maturity.

Previous research on skills and technological change has not provided a satisfactory explanation of how skill requirements are mapped to specific tasks (Martinaitis et al. 2021) or how skills are considered as expandable in nature. By analysing skills-to-job mismatches as a consequence of workplace digitalisation, our study provides a more pertinent consideration of the concept of skills. Nevertheless, there is also still ample scope for the important yet unsolved question of which are the specific domains driving the skills-to-job mismatches and whether they vary across occupations and sectors.

If the debate is to be moved forward, a better understanding of the differential impact of technology on skills and potential mismatches needs to be developed. While mainstream discourses assume that digitalisation leads to underskilling and therefore an increasing need for upskilling (Schlogl et al. 2021), empirical evidence on the direct impact of technology adoption in the workplace on skill requirements remains limited. This stands in stark contrast to the reskilling narratives (Gobena 2024) and the lifelong education and learning policies that are particularly committed to continuous skills development; these can be seen in European Union policies, including the Europe 2020 goals and the more recent European Year of Skills 2023, which includes improvement of adults' digital skills (Brandi et al. 2023). To facilitate a more informed debate on the implications of digital technologies, both sides of skills mismatches must be addressed.

Regarding underskilling, it is not always clear whether we should evaluate the driving tension forces positively or negatively. While formal further training continues to be a central policy instrument for reskilling and upskilling (European Commission 2022), several scholars have highlighted the role of workplaces as learning places (De Grip 2008). Indeed, new technologies invite workers to adapt their skills to new requirements and tasks. In this sense, underskilling may also reflect a temporary adjustment phase in which workers develop the skills required by changing workplace demands. Considering the expandable nature of skills (Dhondt et al. 2021), workplaces with technological changes may function as the space for the expansion of workers' human capital. This view is supported by scholars who suggest that on-the-job learning may

be even more important for workers' human capital development than formal training (De Grip 2024).

Nevertheless, technology-induced changes imply that under-skilled workers will need to adapt to higher demands with risks of higher workload and negative outcomes, particularly if this is not accompanied by sufficient opportunities to update the required skills. On the one hand, there is some evidence that underskilled older workers experiencing skill obsolescence appear to learn more on the job and participate more often in training (Allen and de Grip 2012). On the other hand, research also indicates that underkilled workers are less likely to receive employer-supported training compared to their skill-matched peers (Desjardins and Rubenson 2011). Overall, policies tailored to upskilling still require much more evidence to evaluate the role of underskilling for workers. While this study accounts for workers' participation in further training and highlights the potential of workplaces as learning environments, a promising avenue for future research lies in examining how organisations vary in supporting skill development. Some companies may actively invest in upskilling their workforce, while others may lack the resources or incentives to do so. As companies differ in their skill development and training strategies, resources, and support mechanisms, an unresolved yet decisive question is how this heterogeneity shapes the relationship between digital technologies and skills mismatches.

Overskilling is much more straightforward to evaluate, given that it is intrinsically negative that workers underutilise their skills at jobs. Workplaces in which workers are overskilled impede the acquisition of new skills; this can have a detrimental effect, particularly in the context of cognitive decline (De Grip et al. 2008). Overskilling is especially detrimental given the role of learning from job tasks and learning by doing for workers' human capital development (De Grip 2024). Assuming that skills used at work are job resources (Bakker and Demerouti 2017) and an intrinsic aspect of job quality positively affected by computerisation (Felstead et al. 2019), then under-utilisation of skills through overskilling is clearly an outcome to be avoided.

The novel evidence on overskilling presented in this study contributes to the literature by offering a more nuanced perspective on the often negative-connoted debate on the effects of technological change on workers.

Furthermore, our findings indicate that there is a need to consider the effect heterogeneity when analysing the impact of digital technologies in companies. Adopting digital technologies is associated with a lower probability of workforce skills being underutilised, particularly in economic sectors that have not yet reached a fully mature digital state. Conversely, the positive correlation between technological adoption and underskilling appears to be equally strong across all economic sectors, irrespective of the existing level of digital technologies. Consequently, the initial stages of policy initiatives designed to reduce overskilling should be concentrated on less digitally mature economic sectors.

Finally, in contrast to the traditional frameworks such as the task approach, we propose contextualising debates on new

technologies with skills-to-job mismatches. This should be a robust strategy that allows for a dynamic and adaptive approach to studying ongoing technology adoption. The specialised literature on mismatches has already called for the updating of frameworks, given that technological developments are not necessarily an incessant force that create demand for higher skills (Brunello and Wruuck 2021). The previously assumed expectation that computer technologies will replace routine tasks—rather than cognitive, non-routine tasks (Frey and Osborne 2017)—may not necessarily hold in the wake of recent innovations in artificial intelligence (Autor 2024; Brynjolfsson and Mitchell 2017).

6 | Conclusion

This study examines the relationship between the adoption of digital technologies and skills-to-job mismatches by arguing that research on workplace digitalisation can benefit from an integration with the skills-to-job mismatch literature. While previous research on technological change has predominantly focused on tasks, occupations, or employment structures, the skills mismatch approach adopted in this study directs attention to how technological change reshapes the relationship between workers' skill endowments and workplace skill requirements. In doing so, digitalisation is conceptualised not merely as a process of task substitution, but as a dynamic transformation of skill demands and skill utilisation within workplaces.

Using linked German individual- and establishment-level data, and developing an entropy balancing method, the results suggest that workplace technological adoption is associated with a higher probability of underskilling and a lower probability of overskilling. These results highlight an important tension within processes of digital transformation. On the one hand, digitalisation appears to generate new skill demands and adaptation pressures for workers. On the other hand, digitalisation may reduce the underutilisation of workers' existing skills by increasing workplace requirements and activating previously unused skills.

Moreover, the findings reveal important heterogeneity across economic sectors with different levels of digitalisation. In less digitally mature sectors, workplace digitalisation appears more strongly associated with lower risks skill underutilisation through overskilling than in sectors with more advanced levels of digital technologies. By contrast, this heterogeneity does not emerge for underskilling, as workplace digitalisation is positively associated with higher underskilling across all economic sectors. Therefore, policies aimed at reducing skill underutilisation may be particularly relevant in less digitally mature sectors, whereas policies supporting skill adaptation and upskilling appear necessary across all sectors.

More broadly, both the theoretical framework and the empirical findings support a dynamic understanding of skills mismatches. Particularly in technologically changing workplaces, underskilling may reflect ongoing processes of workplace learning and necessary skill adaptation. At the same time, the lower risks of overskilling associated with digitalisation highlight the importance of analysing whether workers' skills are effectively used at work. Overall, the study argues for a more nuanced perspective on digital transformation that considers not only the emergence

of new skill demands, but also changing patterns of skill utilisation and workplace learning. The skills-to-job mismatch framework offers a versatile approach for examining a wide array of emergent technologies, including artificial intelligence, and their implications for workplace skill requirements. Ultimately, this study advocates a more systematic integration of skills-to-job mismatch research into debates on the rapid technology-driven transformation of skills and work.

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Conflicts of Interest

The author declares no conflicts of interest.

Data Availability Statement

This paper uses data from the BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2018, doi:10.7803/501.18.1.1.10. The Survey was conducted by the Federal Institute for Vocational Education and Training (BIBB), and the Federal Institute for Occupational Safety and Health (BAuA). The data access was provided via a Scientific-Use-File of the Data Research Centre at the Federal Institute for Vocational Training and Education (BIBB-FDZ). This paper additionally uses data from the BIBB Training Panel—An Establishment Panel on Training and Competence Development 2018, doi:10.7803/371.18.1.2.10, which was conducted by the BIBB.

Endnotes

¹An additional, newly developed approach to measuring domain-specific skills mismatch is the job analysis method (Pérez-Rodríguez et al. 2024).

²The value zero is nonexistent, as every surveyed establishment employs at least one digital technology.

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Appendix

TABLE A1 | Digital technologies used to measure the level of digital technologies at companies (subsequently aggregated at economic sectors).

Non-portable digital information and communication technologies, such as computers, printers and other peripherals.
Digital network technologies to support business and work activities, such as Internet, intranet, e-mail, mobile Internet and content management systems.
Digital technologies that relate to data security and data protection and are usually hardwired into a computer's operating system, such as firewall and antivirus software.
Portable digital information and communication technologies, such as laptops, notebooks, smartphones, cell phones and radios.
Applications related to the digital presence and self-presentation of the company, such as company websites, Internet forums and presence on social networks.
Digital technologies specifically related to services for customers, such as online ordering and booking systems as well as online commerce (so-called business-to-customer e-commerce), customer loyalty, customer care (customer relationship management (CRM)) and comparable applications.
Digital technologies that relate to the collection, storage and processing of large amounts of data, such as Big Data, cloud computing and in-house data base systems.
Individual security technologies tailored to specific needs, such as VPN client, encryption technologies (encrypted USB sticks/hard drives/e-mails) and secured server rooms.
Human resources or work organisation-related technologies, such as human resources management tools, building facilities management tools, controlling tools, quality management and the use of crowd-working and collaboration platforms.
Non-sensor-based computer-controlled equipment and digital working tools or means for the creation of products and services, such as machine tools, CNC machines and CAD.
Digital technologies specifically related to networking with suppliers and between businesses, such as enterprise resource management (ERP), supply chain management (SCM), and B2B e-commerce.
Sensor-based computer-controlled equipment and digital working devices or tools for the creation of products and services, such as measuring, analysis and diagnostic devices, low-maintenance production systems, robotics and tracking systems.
Own offer or use of smart services and browser-based services that allow purpose-bound temporary use of analysis and maintenance software for a fee, e.g. service platforms such as Amazon Web Services, Google Cloud Platform and Microsoft Azure.
Digital technologies that operate relatively autonomously and independently of employee operation, such as smart factories, Internet of Things and cyber-physical systems.

Source: BIBB Training Panel 2018.

TABLE A2 | Results for the introduction of new computer programmes on skills mismatches (AME), including a control variable for the dominant task category in jobs.

	Skills match	Overs- killing	Unders- killing
Introduction new computer programmes (vs. no introduction)	−0.015 (0.008)	−0.024* (0.007) **	0.040*** (0.008)
Level of digital technologies in sectors	0.006 (0.004)	−0.006 (0.005)	0.000 (0.003)
<i>Dominant task category (ref. routine manual)</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Routine cognitive	0.008 (0.018)	−0.003 (0.015)	−0.006 (0.021)
Interactive	0.005 (0.018)	−0.010 (0.018)	0.005 (0.021)
Non-routine manual	0.014 (0.021)	0.007 (0.023)	−0.021 (0.024)
Non-routine cognitive	0.024 (0.019)	−0.043* (0.012) **	0.019 (0.019)
Women (vs. men)	−0.000 (0.010)	−0.005 (0.008)	0.006 (0.009)
Further training participation (vs. no participation)	0.017* (0.008)	−0.054* (0.007) **	0.037*** (0.007)
Tenure (years)	0.001* (0.000)	−0.003* (0.000) **	0.003*** (0.000)
Migration background (vs. no migration background)	−0.064* (0.012) **	0.037*** (0.009)	0.026* (0.013)
<i>Level of education (ref. no degree)</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
VET degree	−0.102* (0.018) **	−0.031* (0.014)	0.133*** (0.017)
University degree	−0.060** (0.022)	0.067*** (0.016)	−0.007 (0.020)
<i>Job requirement level (ref. unskilled tasks)</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Skilled tasks	0.109*** (0.018)	−0.174* (0.019) **	0.064*** (0.019)
Complex tasks	0.196*** (0.021)	−0.269* (0.027) **	0.073** (0.023)

(Continues)

TABLE A2 | (Continued)

	Skills match	Overs- killing	Unders- killing
Highly complex tasks	0.181***	−0.289* **	0.109***
	(0.024)	(0.025)	(0.020)
<i>Occupations (ref. raw materials extraction occupations)</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Occupations in machining, processing and repairing	0.088	−0.010	−0.078
	(0.086)	(0.023)	(0.073)
Occupations in machinery and equipment control and maintenance	0.051	0.009	−0.060
	(0.084)	(0.024)	(0.071)
Goods trade, distribution	0.049	0.066**	−0.115
	(0.082)	(0.023)	(0.072)
Traffic, storage, transportation, security	0.071	0.055	−0.126
	(0.086)	(0.030)	(0.076)
Catering and cleaning occupations	0.056	0.055*	−0.111
	(0.092)	(0.025)	(0.077)
Office and commercial service occupations	0.078	0.014	−0.092
	(0.085)	(0.022)	(0.073)
Technical and scientific occupations	0.052	0.016	−0.067
	(0.086)	(0.024)	(0.076)
Legal, management and business occupations	0.075	0.015	−0.090
	(0.091)	(0.023)	(0.078)
Arts, media, humanities and social science occupations	0.054	0.068*	−0.123
	(0.085)	(0.027)	(0.080)
Health and social occupations, care	0.052	−0.026	−0.026
	(0.084)	(0.022)	(0.073)
Teaching occupations	0.032	−0.001	−0.031
	(0.087)	(0.023)	(0.075)
<i>Company location (ref. Schleswig-Holstein)</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Hamburg	−0.009	0.042*	−0.033
	(0.034)	(0.017)	(0.026)
Lower Saxony	−0.001	−0.009	0.010
	(0.025)	(0.015)	(0.020)
Bremen	−0.026	0.039	−0.013
	(0.054)	(0.040)	(0.033)

(Continues)

TABLE A2 | (Continued)

	Skills match	Overs- killing	Unders- killing
North Rhine-Westphalia	−0.034	0.009	0.026
	(0.024)	(0.015)	(0.022)
Hesse	−0.062*	0.022	0.040
	(0.029)	(0.016)	(0.028)
Rhineland-Palatinate	−0.009	−0.009	0.018
	(0.025)	(0.018)	(0.026)
Baden-Wuerttemberg	−0.043*	0.017	0.026
	(0.019)	(0.013)	(0.018)
Bavaria	−0.034	0.002	0.031
	(0.027)	(0.015)	(0.026)
Saarland	−0.021	−0.008	0.028
	(0.045)	(0.031)	(0.037)
Berlin	−0.061	0.009	0.052
	(0.036)	(0.014)	(0.044)
Brandenburg	−0.026	−0.015	0.041
	(0.027)	(0.017)	(0.032)
Mecklenburg-Western Pomerania	0.016	−0.015	−0.002
	(0.036)	(0.023)	(0.028)
Saxony	−0.005	0.003	0.002
	(0.045)	(0.021)	(0.035)
Saxony-Anhalt	−0.031	0.021	0.011
	(0.044)	(0.023)	(0.038)
Thuringia	0.001	0.005	−0.006
	(0.042)	(0.016)	(0.044)
<i>N</i>	15,742	15,742	15,742

Note: Coefficients are AME from multinomial logit regression of the introduction of new computer programmes on skills mismatches with interaction effects between introduction of computer programmes and level of digital technologies in sectors. Entropy-balanced weighted results. Significance levels: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors in parenthesis. Sample includes workers aged 18–65 years.

Source: BIBB/BAuA Employment Survey 2018 and BIBB Training Panel 2018. Author's calculations.

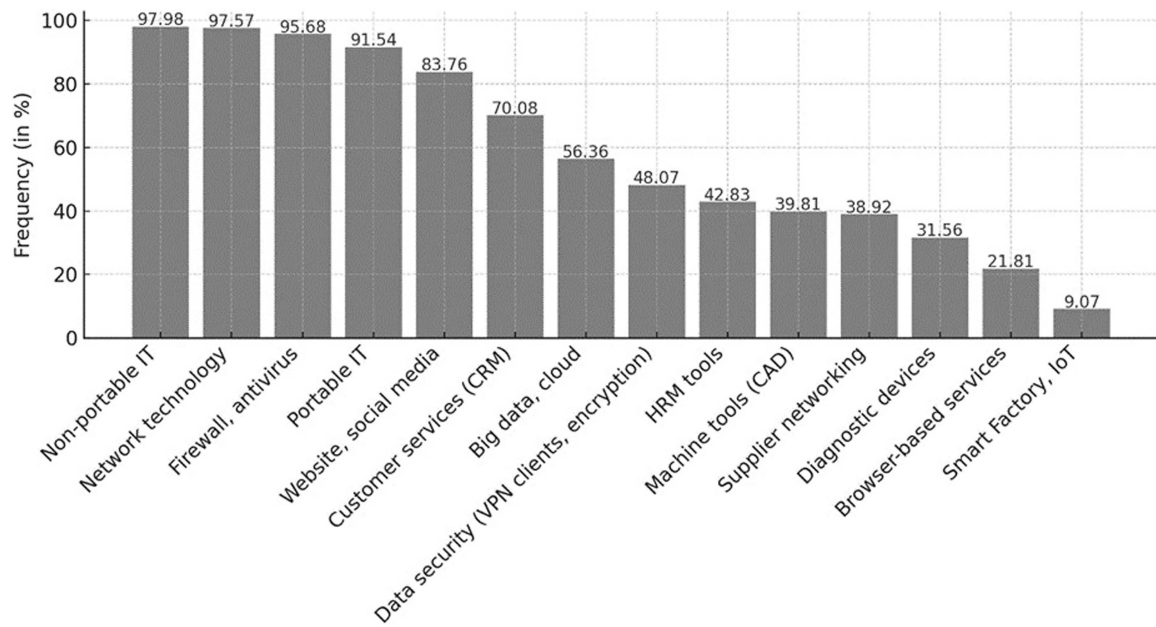


FIGURE A1 | Frequency in use of digital technologies in the working sample (in percent). *Source:* BIBB Training Panel 2018. Author's calculations.