Paper 3 Do employees with specific skill profiles receive more employer-funded training during technological change? Evidence from employer-employee data

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Abstract

Previous work has argued that routine-based tasks put employees into an especially vulnerable situation during digitalisation – they would need to adapt most strongly to new tasks but receive fewer employer-provided training than other groups. This paper focuses on a separate reason for vulnerability, namely skill specificity. A skill profile is measured in this paper as the bundle of tasks an employee conducts on a regular basis. The skill specificity is defined following the skill-weights approach and calculated in a novel way applying the Mahalanobis distance. Based on David Marsden's account of the employment relationship, it is argued that digitalisation calls for more training to attain a skill profile acceptable by the employer and at the same time specific skill profiles reduce employee's bargaining power. Resulting hypotheses are confirmed in panel regressions with data from the German employer-employee panel "WeLL". Most importantly, when the work of employees with specific skill profiles is affected by different forms of digitalisation, we find these employees to receive less employer-financed training than employees with general skill profiles. Strong skill specificity is also associated with high wage losses after job change – and it is also correlated with routinization. In sum, this paper demonstrates that skill specificity significantly adds to an employee's labour market vulnerability in the digitalisation process and is entangled with routinization of tasks.

Keywords: specific skills, mobility, technological change, education, training, inequality
JEL-Classification: J24, J62, O33, J20, I24, M53

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1 Introduction

Which employee characteristics represent advantages or disadvantages for employees in times of digital transformation is an important question to avoid hurdles and possible drawbacks for employees, employers and society as a whole. One strand of literature that deals with answering this question is the task-based approach. In addition to individual competencies, this research focuses primarily on the execution of routine tasks as a risk factor (Autor et al., 2003; Frey & Osborne, 2013; Goos et al., 2014; Vries et al., 2020). A high proportion of routine tasks increases the likelihood that activities will be automated, leading to a greater need for further training. However, these workers have been shown to receive less employer-funded training, resulting in a particularly high risk (Heß et al., 2019; OECD, 2021; Tamm, 2018). This paper considers another risk factor that could bring very similar drawbacks but has been little studied in the literature: the specificity of skill profiles.

Skill specificity is defined in this paper according to the skill weights approach (Lazear, 2009), which classifies skill profiles of workers as specific if the task bundle is very unusual for the labour market and as general if many jobs with similar task profiles exist. According to this definition, skill specificity affects the flexibility and mobility of employees on the labour market. Workers with very specific skill profiles therefore face correspondingly longer periods of unemployment and wage losses when they lose their jobs (Eggenberger et al., 2018; Geel et al., 2011; Lamo et al., 2011; Rinawi & Backes-Gellner, 2018; J. Sanders & Grip, 2004; Silos & Smith, 2015). To compensate for this low flexibility, these employees need more training to adapt to the new requirements resulting from digitalisation (Bechichi & Jamet, 2018; Bechichi et al., 2019).

However, it can be assumed that, similar to routine activities, employees with specific skill profiles will receive fewer further training measures from their employers in times of digital change. Reasons for this are provided by David Marsden's theoretical considerations on employment relationships (Marsden, 1999, 2000, 2015). According to this theory, possible reasons for a reduced willingness to invest on the part of employers are the low bargaining power of employees with specific skill profiles due to fewer outside options on the labour market and expected high training costs.

The paper tests this theoretical assumption and empirically analyses the extent to which employees with a specific skill profile receive employer-financed training measures when they are affected by digitalisation. For this purpose, random-effect-within-between estimations are carried out using the panel data set "WeLL - Further Training as a Part of Lifelong Learning".

The results confirm the expected relationship. Employees affected by digitalisation with very specific skill profiles receive less employer-funded training on average than their colleagues with more general profiles. This lack of training indicates a double burden for employees with specific skill profiles during technological change: less flexibility and less employer-financed training. The otherwise existing advantage of specific skill profiles, such as low replaceability (Becker, 1962), thus seems to become a disadvantage for employees in times of digital change. Possible consequences may include wage losses and rising unemployment (Lamo et al., 2011).

Moreover, descriptive statistics also show a medium-sized, statistically significant positive correlation between skill specificity and the proportion of routine tasks. In other words, the degree of routinization of jobs is statistically related to skill specificity but it is still a separate job characteristic. This could reveal an additional burden for people with routine tasks.

Beside these results, the paper also provides methodological extensions. While the literature on skill specificity mostly conducts studies at the occupational level (Bechichi & Jamet, 2018; Bechichi et al., 2019; Eggenberger et al., 2015; Geel et al., 2011; Neffke et al., 2022), the analysis in this study is conducted at the individual level to investigate whether the receipt of training depends on the specificity of individual skill profiles. For this purpose, the paper extends the existing method for measuring skill specificity by using an alternative distance measure, the Mahalanobis distance (Mahalanobis, 1936). The individual level data also enables to compare not only the skill profiles between occupational groups, as has been done in the literature to date but also different profiles within occupational groups (ISCO-digit 1). The extension of the reference group is particularly important in the context of digitalisation, since technological change does not immediately endanger entire occupational groups, so that it is of particular importance for employees to be flexible within their own occupational group (Arntz et al., 2019; Autor, 2015).

To summarize, in addition to these methodological contributions, the paper contributes to the literature of the task-based approach by examining the rarely considered risk factor of specific skill profiles. While it is already known in literature that less flexibility in times of digital transformation leads to hurdles and an increased need for further training, the results of this paper reveal that this need may not be sufficiently met by employer-financed training. In addition, positive correlations are found with other risk factors such as routine tasks and low skill levels, which may imply additional hurdles. The results therefore highlight the importance of the risk factor of specific skill profiles for employees, employers and policy makers to systematically counteract possible disadvantages.

2 Literature and hypotheses

2.1 Task-specific skill profiles call for more training investments on the part of employers

The considerations of this article are based on the literature on task-specific human capital (Balmaceda, 2006; Gibbons & Waldman, 2004; Schulz et al., 2013) and on the skill-weights approach of Edward Lazear (Lazear, 2009). The theories assume that task specificity can affect employees labour market flexibility or mobility and the retention of training (Gathmann & Schönberg, 2010; Geel & Backes-Gellner, 2011; Poletaev & Robinson, 2008). These two aspects are important because they influence the workers' adaptability to the changing work demands of digital change, the flexibility of firms and economic stability.

According to the theory of task specificity, human capital is specific to the nature of work, not specific to a firm, occupation or industry (Gibbons & Waldman, 2004; C. Sanders & Taber, 2012; J. Sanders & Grip, 2004). Therefore, the approach must be distinguished from the frequently used firm-specific (Becker, 1962), industry-specific (Neal, 1995; Parent, 2000) and occupation- specific (Nawakitphaitoon, 2014; Shaw, 1984) human capital. When a worker changes their job and is assigned to a new set of tasks, some of the worker's acquired human capital goes unutilized (Gibbons & Waldman, 2004). The amount of unused human capital depends on how similar the work tasks of the old and new job are. If the similarity is very low, it may also be necessary to learn new skills, which leads to a reduction in productivity in the first phase. Therefore, a change to a different employer or job results in lower turnover costs if the task profiles of the old and the new job largely match.

Edward Lazear's skill-weights approach (2009) builds on this concept and suggests a particular understanding of task-specific human capital by defining a skill combination as specific if only a few people in the labour market hold it. Accordingly, the skills themselves are all general in nature; only their combination leads to specificity. Moreover, the skill-weights approach illustrates possible consequences of task-specific skill profiles for employees and employers.

In particular, skill specificity can contribute to higher employee wages because workers are adapted to company-specific tasks that are atypical for the labour market. They are therefore valuable to the company and harder to replace (Gathmann & Schönberg, 2010; Lazear, 2009; Silos & Smith, 2015; Wilmers, 2020). At the same time, however, exactly these aspects also lead to a reduction in mobility. Skill specificity implies that few jobs in the labour market require the same work tasks. Accordingly, there is a high skill distance to the other jobs, which makes it less likely that in case of an involuntary job change the tasks of a new job will match those of the old one (Lazear, 2009). Existing literature on skill distances and mobility confirms this, showing that when the tasks of the new and old job do not match, this will lead to a loss of task-specific human capital and wages (Eggenberger et al., 2015, 2018; Geel & Backes-Gellner, 2011; Neffke et al., 2022; Poletaev & Robinson, 2008; Silos & Smith, 2015). Poletaev and Robinson (2008) even point out that wage losses are more closely related to the change of skills than to the change of profession or industry per se. To sum up, involuntary job changes are more likely to be accompanied by a pay loss and longer unemployment after termination for employees with task-specific skill profiles (Eggenberger et al., 2018; Geel et al., 2011; Lamo et al., 2011; Rinawi & Backes-Gellner, 2018; J. Sanders & Grip, 2004; Silos & Smith, 2015).

Due to decreasing mobility, it is less attractive for employees to invest in specific skill profiles. When they make investments, they may become dependent on their company, as the specific tasks are to some extent company/job-specific. At the same time, the fulfilment of company and job-specific tasks is of particular interest for the company. Therefore, it is plausible to assume that employers who need employees with very specific skill profiles must invest in these employees' further education and training (Lazear, 2009). According to Becker (1962), co-financing of further training is also to be expected, as employees and employers can thus insure themselves against the hold-up problem. So far, only few studies have empirically examined Lazear's prediction but they do find a positive link between employers' investment in training and the specificity of skill profiles (Backes-Gellner & Mure, 2005; Geel et al., 2011).

This relationship between task specificity and employer-provided training can be described formally:

$$T_p(sp): \mu(sp), \sigma^2 \tag{1}$$

$$\mu(sp) = \mu_0 + a \cdot sp; a \geq 0$$

The probability density function of further training (T_p) depends on the task specificity (sp). Since the slope coefficient a is assumed to be positive, the expected value of further training courses $\mu(sp)$ increases with rising specificity (sp).

In order to expand the rather small research base on this relationship, this paper re-examines the following hypothesis:

H 1: Employees with specific skill profiles receive more employer-financed further training than employees with more general skill profiles.

2.2 Digitalisation associated with more employer-financed training investments

Many studies point to the fact that digital transformation is leading to a change in work requirements and an increasing need for training due to strategic changes (Acemoglu & Restrepo, 2019; Autor, 2015). Digital transformation is understood here in the socio-technical sense as the change in the world of work through the use of new technologies (Hanelt et al., 2020; Strohmeier, 2020). These new technologies can support or replace employees. The process of introducing technologies into companies is referred to as digitalisation. It involves the implementation of information and communication technologies (ICT), software, or new production techniques, machines or materials (Advanced manufacturing technologies – AMT).

Some studies predict that especially low-skilled jobs will disappear through the process of digital transformation, as they involve more routine tasks and can therefore be automated more easily (Acemoglu & Autor, 2011; Frey & Osborne, 2013; Goldin & Katz, 1998). The skill-biased technological change approach assumes that the use of new technology will require a more highly qualified workforce (Berman et al., 1998; Bresnahan et al., 2002; Goldin & Katz, 1998). Others expect a polarization of work (Goos et al., 2014; Spitz-Oener, 2006). Regardless of which scenario occurs, workers will be forced to react flexibly to new work demands. To maintain this flexibility, and to help ensure that digital transformation leads to economic and social benefits, training can make an important contribution (Arntz et al., 2016; Bechichi & Jamet, 2018; Bode & Gold, 2018; Elnaga & Imran, 2013; Lamo et al., 2011; Lukowski et al., 2020). Companies accordingly invest on average more in the further training of their employees when they undergo technological transformation (Gashi et al., 2010; Janssen et al., 2018; Kupets, 2018; Lukowski, 2019; Seyda et al., 2018). Formally, this positive relationship between further training and digitalisation can be presented as follows:

$$T_p(d): \mu(d), \sigma^2 \tag{2}$$

$$\mu(d = 1) \geq \mu(d = 0)$$

The expected value of the number of training courses (μ) is higher when employees are affected by digitalisation (d) than when they are not. Digitalisation thus influences the probability density function ($\mathrm{T}_p(d)$).

A second hypothesis follows from this:

H2: Employees who are affected by the introduction of new ICT or software, or new production techniques, machines or materials need more employer-financed training.

2.3 Less training for affected groups

Although companies do invest in their employees, not all occupational and population groups receive further training to the same extent (OECD, 2021). This can be attributed to different needs, but also to different investment interests of the employer. If employees' work is threatened by digitalisation, they will predictably need more training to compensate for the negative consequences. This especially affects employees whose work tasks can be easily automated and those with low adaptability or mobility, as digitalisation and especially automation increase the number of job and career changes (Bechichi & Jamet, 2018; Nedelkoska, 2013). Moreover, involuntary mobility, unlike voluntary occupational mobility, is usually associated with a loss of task-specific human capital (Robinson, 2018). As a result, employees with task-specific skill profiles are also a group of employees who could be negatively affected by digitalisation due to their low mobility. Therefore, Bechichi and Jamet (2018) and Bechichi et al. (2019) predict a higher need for further training for employees with specific skill profiles in order to change professions and remain employable.

Though the link between skill specificity and the extent of employer-funded training has not been examined directly, some indirect evidence is available. Some studies show that certain groups with high training demand paradoxically receive less training than other groups. In particular, employees with a low skill level (Brunello & Wruuck, 2020; Heß et al., 2019; Mohr et al., 2016; Nedelkoska & Quintini, 2018; OECD, 2021) and with many routine tasks, who face particularly negative consequences from digitalisation, receive less training on average (Heß et al., 2019; Lukowski et al., 2020; Tamm, 2018). Lukowski et al. (2020) also show that companies that undergo digital transformation do not invest more in training when their employees perform routine tasks. Overall, employees who could be particularly negatively affected by digital transformation appear to receive less training on average

These findings can be partly explained by a shift in bargaining power between employers and employees. Leduc and Liu (2019) argue that the higher the threat of automation, the less bargaining power workers have. This shift occurs even though companies have higher incentives to create (more) new jobs after automation processes.

The nature of this shift and the implication for training provision can be derived from a traditional analysis of the employment relationship as an incomplete contract (Marsden, 2000, 2015). Assume an equilibrium in which the employee accepts the employer's assignment of work tasks at a given wage. In Figure 1, equilibrium is possible in the area of potential agreement, the zone is located below the employer's profit curve Sf_0 and above the employee's breakeven curve Sw_0. The shape and position of the break-even curve of the employees are determined by the wage and interest in the work tasks. The shape and position of the employer's profit curve are determined by the potential profit from the performance of the various work tasks. In the area between these curves, the parties are willing to enter into employment. If the parties have agreed on a wage W_A, then the worker accepts management's authority in assigning work tasks, which can lie between A and B, indicating the zone of acceptance. The tasks may differ in terms of characteristics such as skill level or problem-solving requirements.

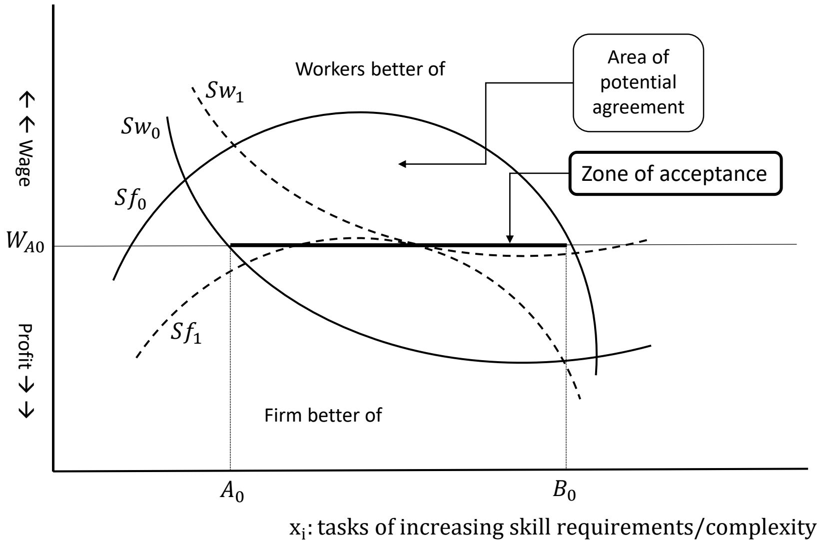

Figure 1 Zone of acceptance of the employment relationship

Source: Own graphic based on Marsden (2015)

Whether this balance is maintained or one party exploits the weaknesses of the imperfect contract by shifting the distribution of tasks to the disadvantage of the other party, depends on various factors. One can be an exogenous shock of digitalisation. The task-based approach and the skill-biased technological change approach predict an increase in skill requirements in the curse of digital change due to the elimination of routine tasks and an increase in complex work tasks (Acemoglu & Autor, 2011; Bresnahan et al., 2002; Frey & Osborne, 2013). Based on this, routine tasks become less profitable, while complex tasks become more important for the company. Therefore, it can be assumed that the introduction of new technologies and the new market requirements due to digitalisation will shift the company's profit curve to the right on the x-axis (Sf_D) (Figure 2). Consequently, the employer will breach the originally negotiated equilibrium and shift it to the right. In the new zone of acceptance, routine tasks will accordingly be dropped, and complex tasks added.

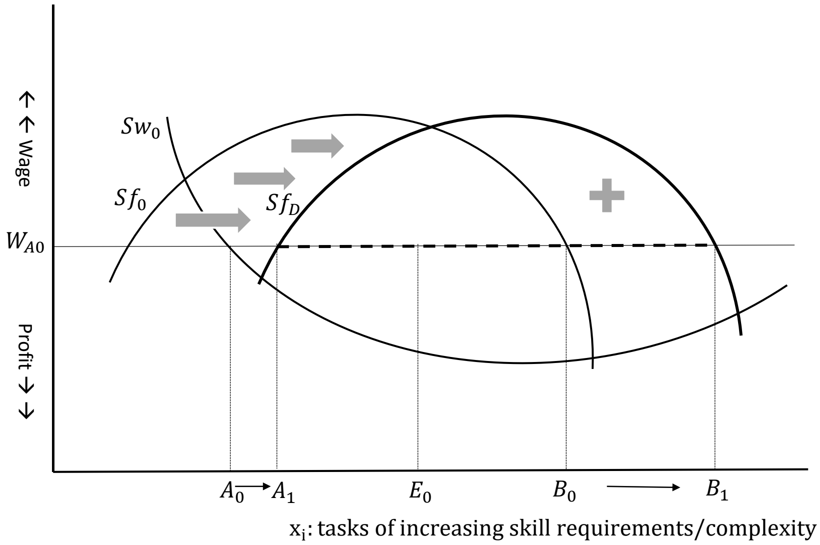

Figure 2 Shift in the firm profit curve due to digitalisation

Source: Own graphic based on Marsden (2015)

How workers react to this violation of the equilibrium depends on both their market situation and their skill set. If the new work tasks correspond to the employee's interests and abilities, the shift of work tasks may not only be in the employer' but also the employee's interest (Figure 2: Sw_0). However, if the employee has a very specific skill profile or a low skill level, the adaptation to the new work tasks may be more difficult (Eggenberger et al., 2018). It is possible that the performance of the new tasks requires competences that the employees do not hold. Then the new work tasks are not completely within the employee's acceptance range (Figure 3: Sw_1). For workers with specific skill profiles, this shift poses a problem for both high and low skill level workers, as in both cases the new work tasks are more likely to be outside the range of acceptance.

Employees for whom the new distribution of tasks is disadvantageous can try to sanction the breach. In this way they can force a return to the original tasks. To achieve this, they can threaten to quit (Marsden, 2015). However, they can only do so if they find alternative job offers on the labour market. For workers with task-specific skill profiles, this is consequently not possible or only possible to a limited extent. The probability that they will have to accept the shift of work tasks is therefore high.

In summary, the shift in the profit curve due to the new market demands of digitalisation poses a particular challenge to workers with specific skill requirements for two reasons and can therefore weaken their bargaining power. Firstly, due to their task-specific skill set, a shift in work tasks is more likely to be out of their skill range and thus out of their range of acceptance. Secondly, due to a lack of employment alternatives, they cannot sanction the violation of the contract. If they do not fulfil the new work tasks, they may be threatened with dismissal.

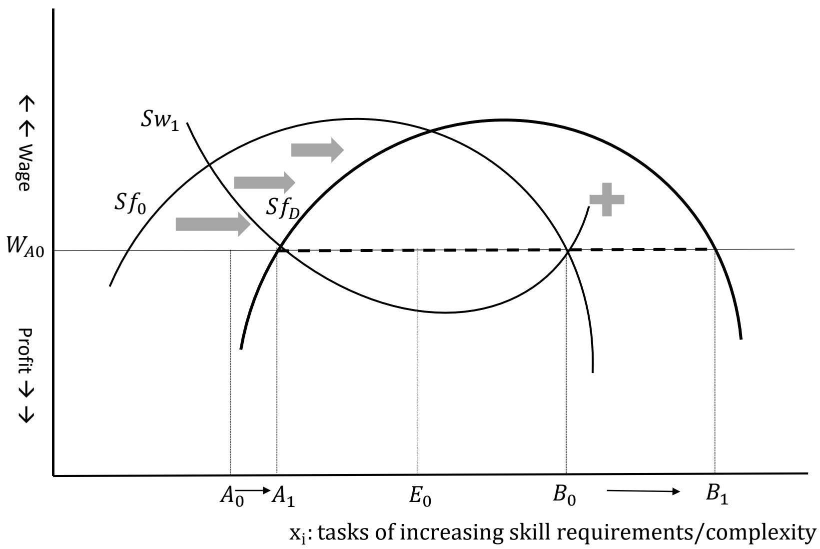

Figure 3 Zone of acceptance for workers with task-specific skill profiles

Source: Own graphic based on Marsden (2015)

If the new work tasks do not fall within the acceptance range because the necessary skills are lacking, the employees must be further trained to enable them to perform the tasks and thus expand the acceptance range. Whether employees receive further training from the employer for this purpose depends on various factors. The following theoretical considerations indicate that the incentive for companies to invest in training for employees with specific skill profiles could be lower than for employees with more general skill profiles due to digitalisation.

1. Since they have limited financial resources due to investments already made in new technology and change processes, companies in the digitalisation process carefully consider in which employees they are willing to invest (Brunello & Wruuck, 2020). The less the new tasks are in the employee’s area of acceptance/competence, the higher the potentially necessary investment in further training. If the employer provides the financing, the employee's salary increases accordingly in the short term, so the company's profit decreases. The company weighs this investment in training against the costs of terminating the existing contract and hiring an employee whose skills already meet the requirements of the job. The more task-specific the qualification profile, the more likely the new tasks resulting from digitalisation will not lie in the original skill area so that the need for training

investments is higher (Eggenberger et al., 2018; Lamo et al., 2011). This can lead to the company's calculative result of not investing in training.

2. Another aspect that explains the employer's willingness to invest in further training is based on Becker’s human capital theory (Becker, 1962). In the equilibrium, according to Becker (1962), both parties anticipate the possibility of the hold-up problem. Employees are therefore only willing to accept the job offer or in this case the new work tasks if they receive more training from the employer in order to remain employable. The employer is willing to invest in training under certain circumstances in order to attract appropriately qualified workers. Due to the shift in the employers’ profit curve through digitalisation, a new equilibrium has to be negotiated. Maintaining this equilibrium is primarily in the interest of the one who has more to lose. The one with the lower risk has the upper hand. This effect is also known as the “principle of lesser interest” (Stinchcombe, 1986). For workers, digitalisation and the associated shift in work tasks pose a serious threat to employment. This is especially true for workers with task-specific skill profiles, as they have fewer job alternatives on the labour market. Accordingly, the employer has the upper hand and the worker has less bargaining power. As a result, the worker is more willing to make concessions in order not to jeopardize the employment relationship. This can lead to fewer benefits in the form of less employer-funded training.
3. Moreover, it is only profitable for employers to invest in training for employees if they stay within the company in the long term, because otherwise the investment will be lost. (Acemoglu & Pischke, 1998; Becker, 1962). Companies also benefit from the long-term employment due to lower transaction costs and increasing worker productivity through learning by doing (Gibbons & Waldman, 2004; Smith, 1776). If the work tasks change quickly, a high specificity of the skill profile can jeopardize long-term employment due to a lack of adaptability. This can lead to a reduced interest in investing in workers with specific skill profiles when change is imminent due to digitalisation.
4. In general, digital transformation demands a high degree of flexibility from the company and thus also from the employees. Normally, in addition to multitasking, the performance of very specific tasks can increase the bargaining power of the employee vis-à-vis the employer, as they are less easily replaceable (Wilmers, 2020). However, in the course of digital transformation and the resulting threat of changes in work tasks, this task-specificity can become a liability for workers when multitasking and general skill profiles become a

success factor (Lamo et al., 2011). If workers are more generally trained and can be deployed more flexibly in the company, this also represents an advantage for companies since internal and external flexibility can increase (Kalleberg, 2003). This makes employees with more general skill profiles more interesting for companies during digital transformation, while those with specific skill profiles become less attractive. As a result, again, employers are less willing to invest in these employees' training.

The relationship assumed on the basis of these arguments can be represented by equation (3). It combines and extends formula (1) and (2).

$$T_p(d, sp) \colon \mu(d, sp), \sigma^2 \tag{3}$$

$$\mu(d, sp) = \mu_0(d) + a(d) \cdot sp$$

The probability density function ($T_p(d, sp)$) of further training now depends on both task specificity (sp) and digitalisation (d). The expected value of further trainings (μ_0) is positively related to digitalisation $\mu_0(d = 1) \geq \mu_0(d = 0)$, as the need for further training increases in the course of digitalisation. However, the theoretical considerations listed above lead to the assumption that the influence of task specificity on training becomes negative with digitalisation.

$$a(d) \begin{cases} \leq 0 \; if \; d = 1 \\ > 0 \; if \; d = 0 \end{cases}$$

The positive effect of digitalisation can thus be reduced or reversed by the negative effect of skill specificity when digitalisation occurs. This leads to the final hypothesis.

H 3: Employees with specific skill profiles participate less often in employer-funded training when they are affected by digitalisation (introduction of new ICT or software/ introduction of new production techniques, machines or materials) than employees with less specific skill profiles.

3 Empirical analysis

3.1 Data and measures

This study uses the factually anonymous data of the Panel “WeLL” – Employer-Employee Survey for the project “Further Training as a Part of Lifelong Learning”. Data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB). This is a longitudinal survey with four survey waves conducted in 2007, 2008, 2009 and 2010. Within the survey 6400 employees from 149 companies in Germany were interviewed by the Institute for Applied Social Sciences (infas).

The companies were selected for inclusion in “WeLL” according to their company size (100 to 199, 200 to 499 and 500 to 1999 employees), sector (manufacturing and services), regional location (Eastern and Western Germany) and their participation in the survey for the IAB Establishment Panel in 2005. A random sample was taken from all employees subject to social insurance contributions in the selected companies.

The microdata set is particularly suitable for this research project because it provides very detailed monthly information on training activities, on work tasks and on how respondents are affected by technological changes. By focusing on data from one country, Germany, possible biases resulting from differences in education systems and differences in occupational groups are effectively controlled.

The data set is used in a balanced form for the REWB and fixed effects estimation. This means that only those respondents are considered who were interviewed in all four survey waves. Since the occupational group of “skilled agricultural and fishery workers“ with 4 respondents and “works and staff councils“ with 8 respondents are only marginally represented in the data set and a calculation of the skill distances would not be representative, the respondents of these occupational groups are removed from the data set for the analysis. This reduces the number of respondents considered in the analysis to 1,902 employees.

Dependent variable

In the following analysis, the monthly training hours in which the respondent participated and which were financed by the employer are considered as the dependent variable (formal and non-formal training). Employees provided information on several training measures in the survey. They were asked who financed the respective training measure and how many hours it covered. If the respondents indicated that the further training was fully or partly financed by the employer, it was added to the number of employer-provided further training courses for the purposes of this paper. No distinction is made as to whether this training was carried out internally within the enterprise or externally. Informal training is not considered here because the focus of the analysis is the general willingness of employers to invest in the further training of certain employees. Hence informal, self-directed learning, though it is often financed by the employer, is not considered here.

Digital transformation of work

Two dummy variables are used to measure how workers are affected by technological transformation. The first variable is based on the question: Has your work situation changed due to operational conditions? Has your work been affected by the introduction of new production techniques, machines, materials? (hereafter abbreviated to **“new technology”**). The second variable is based on the following question of the data set: Has the equipment of your workplace with information and communication technologies changed or do you use new software? (hereafter abbreviated to **“new ICT/software“**) (Appendix A.1.). While the variable "new technology " includes technological changes that mostly affect blue collar workers, the variable "new ICT/software " includes the introduction of new technologies that more often affects white collar workers. The differentiation of the technologies considered here is similar to that of Bayo-Moriones et al. (2017), who highlight the importance of considering these two forms of technology separately. Therefore, by using both variables, possible technological changes for different employment groups can be considered.

Task specificity of skill profiles

Since the operationalization of skill specificity has decisive innovations and differences to previous literature, it will be presented in detail in the following. The differences lie both in the distance measure used (Mahalanobis distance) and the level of observation (individual). Why the change of the operationalization is necessary for the correct analysis of the research question is also explained in more depth.

For theoretical reasons, this empirical study analyses skill distances within the occupational group and at the individual level. Namely, that digitalisation will not necessarily lead to the disappearance of entire professions, but only of certain jobs and work tasks (Arntz et al., 2019; Autor, 2015; Brynjolfsson & Mitchell, 2017). Due to the higher skill similarity, employees would look for alternative employment opportunities mainly in their own occupational group to avoid a loss of human capital (Kambourov & Manovskii, 2009; Poletaev & Robinson, 2008). Especially against the background of digital transformation, job changes within one's own occupational group are important and should not be neglected. However, studies on the topic of skill distances and mobility focused on job mobility *between* occupational groups. Therefore, unlike previous work, this paper focuses on the skill distance to one’s own occupation.

In order to consider the specificity to one's own occupational group, an analysis on an individual level is required. In contrast to analysis at the occupational level, it is not necessary to calculate an average of the skills of workers belonging to an occupational group when using individual profiles. The averaging process is disadvantageous because it ignores the actual skills of the individual worker, even though skills can vary widely within the occupational group (Arntz et al., 2016; Nedelkoska & Quintini, 2018). The use of individual skill profiles thus provides crucial additional information that has so far been disregarded by most research on skill distances.

Existing studies used different calculation methods to determine the skill distances between occupational groups: the Euclidean distance (Poletaev & Robinson, 2008), cluster analyses (Geel & Backes-Gellner, 2011) and the angular distance (Bechichi & Jamet, 2018; Bechichi et al., 2019; Gathmann & Schönberg, 2010). The distance measures listed are certainly suitable for calculating skill distances between occupational groups. However, they are not appropriate for the purposes of this paper as they cannot determine the distance of an individual skill-vector within a distribution of vectors properly. For this reason, the Mahalanobis distance is applied for skill distance analysis in this paper (Maesschalck et al., 2000; Mahalanobis, 1936). The Mahalanobis distance is often used in a statistical context to determine outliers and for cluster analysis but also for many other applications of distance calculation (Mahalanobis, 1936; Penny, 1996). Therefore it is used in various fields – for example Machine learning (Xiang et al., 2008), or biology (Farber & Kadmon, 2003) – and shows various advantages over other distance measures. Nevertheless, it has not been used hitherto in the field of skill distance calculation.

The main advantage of the Mahalanobis distance is that by considering the variance-covariance matrix, it not only provides information about individual skill distances, but also about the distribution of the skill profiles. Thus, for each individual skill vector, it can be determined whether it lies outside, at the edge or in the middle of the distribution. If the vector lies outside the distribution, the distance to the other skill vectors in the sample is rather large (specific skill profile). Consequently, the number of job alternatives is small, as there are few skill vectors in the vicinity. If the skill vector is in the middle of the distribution, it means that many of the workers have a similar task profile, which implies that there are more alternative employment opportunities (general skill profile). A special advantage of the Mahalanobis distance is also that it is able to determine distances between points of several variables, even if they are correlated. The Mahalanobis distance can be calculated using the following formula:

$$d_M = \sqrt{(X - \bar{X})\Sigma^{-1}(X - \bar{X})^T} \tag{4}$$

The tested point X is an n-dimensional vector and the distribution is described by the vector of the average values for all variables $\bar{X}$ (so called centroid) and the covariance matrix Σ.

The employees' skill vectors used for the calculation consist of 12 different work tasks, for which the respondents had to indicate on a 3-step scalar how often they perform them (see Figure 4, Appendix A.2.). The more dissimilar the vectors, the higher is the specificity of the individual skill profile. Specificity is determined by the distance between the individual skill profile (X) and the other skill profiles of the same occupational group. The calculated **"skill distance"** is standardized for all occupations simultaneously so that it is easier to make statements about the degree of specificity compared to other employees. A standardized distance value of zero corresponds to the mean value of all distances. If the standardized distance value is below zero, the skill specificity is below the average value. Mobility is accordingly higher, while a distance value above zero indicates lower mobility.

After explaining how skill specificity is calculated, we will discuss why it is appropriate for this study to use Mahalanobis distance rather than Euclidean distance to measure the specificity of skill profiles. Figure 4 illustrates that the Mahalanobis distance (elliptical lines) is oriented towards the distribution. The Euclidean distance (dashed line and arrows), on the other hand, only determines the distance to the mean. Therefore, the example vector (1) would have a much lower skill specificity and higher mobility according to the Euclidean distance than vector (2). Using the Mahalanobis distance, on the other hand, it becomes clear that vectors (1) and (2) have the same distance to the distribution and have an identical number of job switching possibilities. The Euclidean distance would calculate the same skill specificity for all vectors on the dashed line, although it is obvious that the vectors on the dashed line have a very different number of job alternatives.

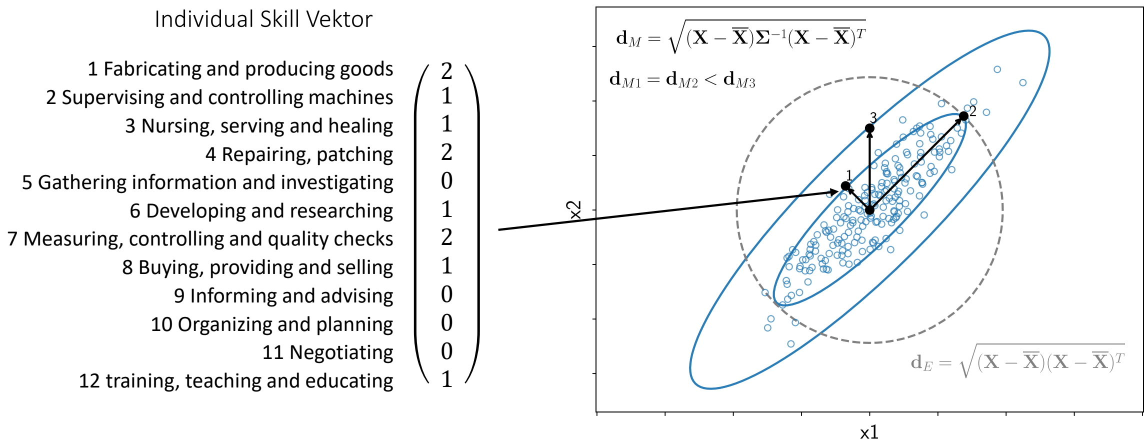

Figure 4 Mahalanobis distance

In summary, using Mahalanobis distance and looking at it at the individual level and within occupational groups can add to and extend the existing literature on skill specificity (skill distance) and mobility.

Control variables

The variable **"ICT intensity"** is used as a control variable and takes on the value 1 to 4 indicating the number of ICTs used. Correspondingly 1 means that the respondent has indicated to use one of the four ICTs: computer, internet, mobile phone or e-mail. A value of 4 means that the respondent has used all four ICTs. There is no weighting of the different ICTs. We control for the level of ICT-use, as it can lead to an increased number of training courses and the use of ICT can facilitate product and process innovation (Chen et al., 2017; Hempell & Zwick, 2008).

As part of the model, the variable **"routine tasks"** is used to control the proportion of routine tasks performed by the employee. Two basic findings of the literature of the task-based approach indicate that the consideration of routine tasks is important for the investigated context. Firstly, routine tasks performed by workers can be more easily replaced by the introduction of technology than non-routine tasks (Autor et al., 2003; Frey & Osborne, 2013; Goos et al., 2014; Vries et al., 2020). Secondly, the proportion of routine tasks a person performs can influence the number of training courses –people with more routine activities receive on average less further training than people with less routine activities (Heß et al., 2019). Therefore, the literature indicates that the number of routine tasks a person performs can influence the number of training courses and also affects the extent to which people are affected by technological change. By including the amount of routine activities as a control variable, an omitted variable bias is prevented. There is another reason why it is important to examine whether routine tasks are correlated with the main explanatory variable, skill distances. When facing technological change, workers with routine tasks tend to receive less training, and so do workers with task-specific skills if the hypothesis is correct. Hence, if routine tasks also tend to be specific, then this would pose a double threat to respective workers, a threat that is of considerable public policy interest.

Since the share of routine tasks is not available as a variable in the data set, it is calculated from the information on the work tasks following the method suggested by Tamm (2018). The 12 skills of the “WeLL” dataset are classified into the five task categories – routine manual, non-routine manual, routine cognitive, non-routine analytic, and non-routine interactive – and a routine index is calculated according to the calculation scheme of Spitz-Oener (2006):

$$Routine\ tasks = \frac{Number\ of\ activities\ in\ task\ category\ "routine\ manual"\ frequently\ performed\ by\ worker\ i}{Total\ number\ of\ job\ activities\ in\ category\ "routine\ manual"}$$

Since there are only two different tasks in the manual routine tasks category, the value of the routine tasks becomes 1 if the person performs both activities frequently, it takes the value 0.5 if the person performs one of the two activities frequently and 0 if none of the routine manual tasks are performed.

A number of other control variables that do not change over time are included: the year of birth (1952-1961, 1962-1971, as of 1972; reference category: until 1951) as the amount of training can vary with age (Grund & Martin, 2012), Western Germany (reference category: East Germany) because of the systematic training differences in West and East Germany (Leber & Stegmaier, 2013), German citizenship (reference category: other nationality) because non-

German citizens may receive a higher level of training, e.g. additional language courses. In addition, dummies for the firms were included in the regression to control for differences in firm- and sector-specific training policies (Grund & Martin, 2012).

Moreover, the following control variables, which change over time, are considered because they may have a systematic effect on the amount of employer-financed further training: gross monthly wages (500-1000€, 1000-1500€, 1500-2000€, 2000-2500€, 2500-3000€, 73000-4000€, 84000-5000€, 95000€ and more; reference category: less than 500€) (Mohr et al., 2016), the number of weekly working hours (numerical) (Bilger et al., 2018), year dummies, the ICT intensity (ICT Intensity 2=two ICTs used, ICT Intensity 3=three ICTs used, Intensity 4=four ICTs used; reference category: zero or one ICT used) (Chen et al., 2017; Hempell & Zwick, 2008), job status (worker, marginally employed, others; reference category: employee) (Grund & Martin, 2012) and fixed-term employment contract (reference category: permanent employment contract) (Jenkins & Wolf, 2004).

3.2 Descriptive statistics

Whether the calculated skill distances are actually related to employee flexibility/mobility can only be examined for internal mobility in this paper. To map internal mobility in the data set, employees were asked whether they changed their jobs within the company. The descriptive evaluation of this aspect shows that employees who have changed jobs internally have, on average, significantly lower task distances and thus more general competence profiles (shown graphically in Figure 4). This suggests that, as expected, the skill specificity measured here is related to employees' internal flexibility.

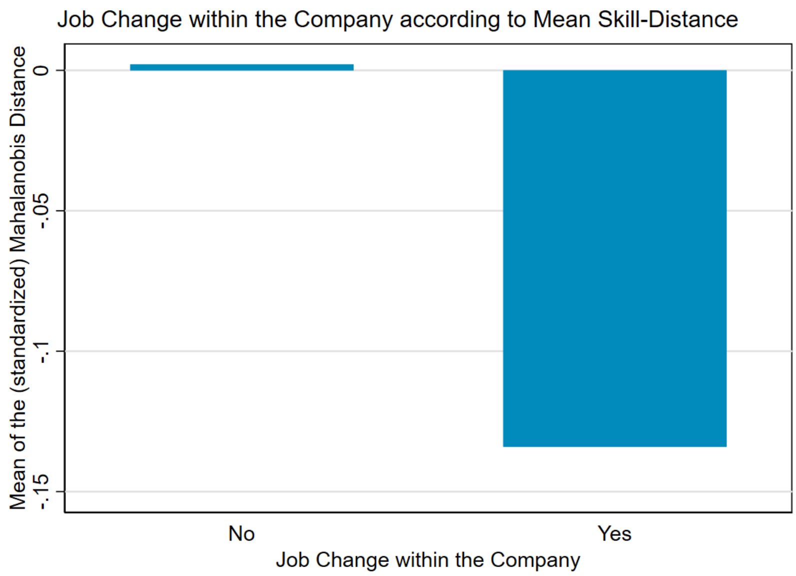

Figure 5 Internal mobility and skill specificity

Source: Own calculations based on WeLL data by Institute for Employment Research

Since no mobility data on the external labour market is available, it is not possible to comprehensively evaluate the relationship between the determined skill distance and external flexibility/mobility. But even though external mobility cannot be verified in the context of this study empirically, the results from existing literature indicate a relationship between specific skill profiles and the external mobility (Eggenberger et al., 2018; Geel & Backes-Gellner, 2011). Since the new measurement method does not change the general theoretical idea of measuring task specificity, but mainly provides more accurate results at the individual level, it can be assumed that the relationship could also apply to the specificity values determined in this paper.

Based on the distribution of the specificity of the skill profiles, conclusions can be drawn about the mobility of employees in the various occupational groups. Figure 5 illustrates the mean values of the standardized skill-profile-specificity for the different occupational groups (ISCO-88 one digit) on a descriptive basis. The distances correspond to the average skill distance that an employee has to overcome when he or she changes jobs within the occupational group. It can be seen that there are considerable differences in the average skill-specificity between the occupational groups. Ranging from a mean value of the standardized skill distance of -0.1804 “legislators, senior officials and managers” to 0.2307 “service workers and shop and market sales workers”. Switching jobs within the occupation seems to be particularly difficult for “service workers and shop and market sales workers” (0.2307), “craft and related trades workers” (0.1414) and “plant and machine operators and assemblers” (0.2202) while it is easier for “legislators, senior officials and managers” (-0.1804) and “professionals” (-0.1583).

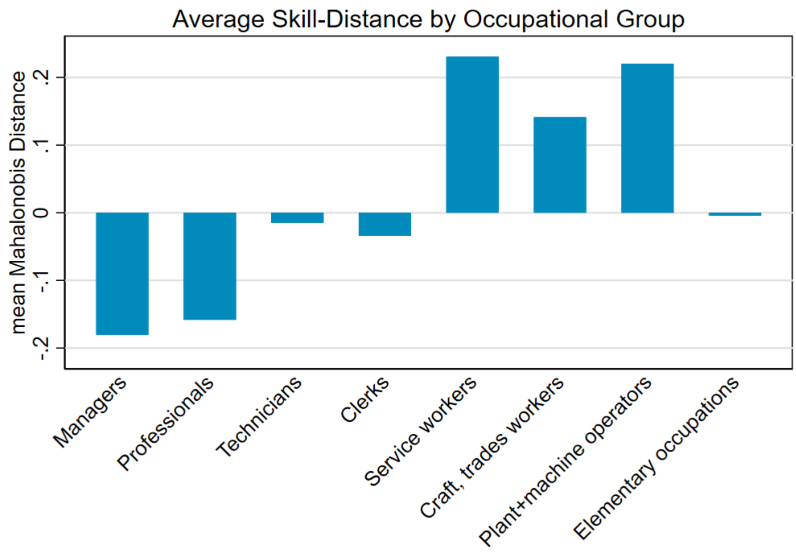

Figure 6 Mean values of the skill specificity (within the occupation) by ISCO-88 one-digit occupational group

Source: Own calculations based on WeLL data by Institute for Employment Research

Note: Occupational groups “works and staff councils“ and “skilled agricultural and fishery workers“ not considered due to insufficient data

Based on the ISCO-Skill-Level Classification (Elias, 1997), the occupational groups displayed can be assigned to four skill levels (see Appendix Table A.3., which shows the distribution of specificity for the employees of the different skill levels). The classification of occupations into the various ISCO-Skill-Levels is based on task complexity and skill/education level. The fifth category shown here includes legislators, senior-officials and managers who are not assigned to a skill group within the ISCO-Skill-Classification. Figure 6 illustrates that people with rather low skill requirements (Skill-Level 1-3) have more task-specific skill profiles on average, while those with a higher skill level (4, 5) have more general skill profiles. This suggests that it is easier for people with higher skill levels, who typically perform problem-solving, decision making and creative tasks, to change jobs within their occupational group than it is for employees with a lower skill level, who typically perform simple and routine physical or manual tasks. It seems particularly difficult to change jobs within the occupational group for people in the second skill category.

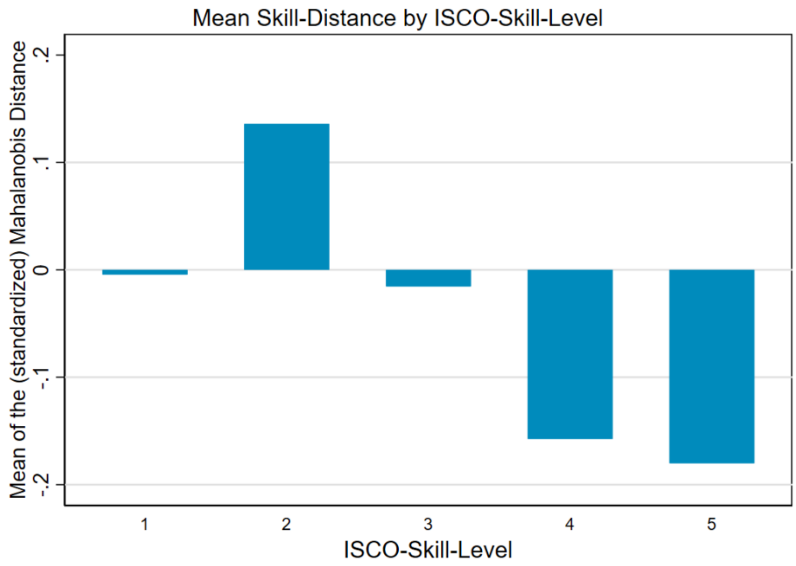

Figure 7 Mean values of the standardized skill specificity by ISCO-Skill-Level

Source: Own calculations based on WeLL data by Institute for Employment Research

Extant literature shows that especially people with many routine tasks are threatened by job loss through automation (Autor et al., 2003; Blien et al., 2021; Frey & Osborne, 2013; Goos et al., 2014). It is therefore interesting to examine how often people with specific skill profiles also perform routine tasks. In order to investigate whether people with specific qualification profiles perform routine activities more frequently, the Routine Intensity Index of Miroudot et al. (2016) is used. This index assigns a factor to different occupational groups which indicates how often routine tasks are performed. Figure 8 illustrates that people with more specific skill profiles are on average more likely to work in occupations with more routine tasks. This is of course only a correlative and no causal finding.

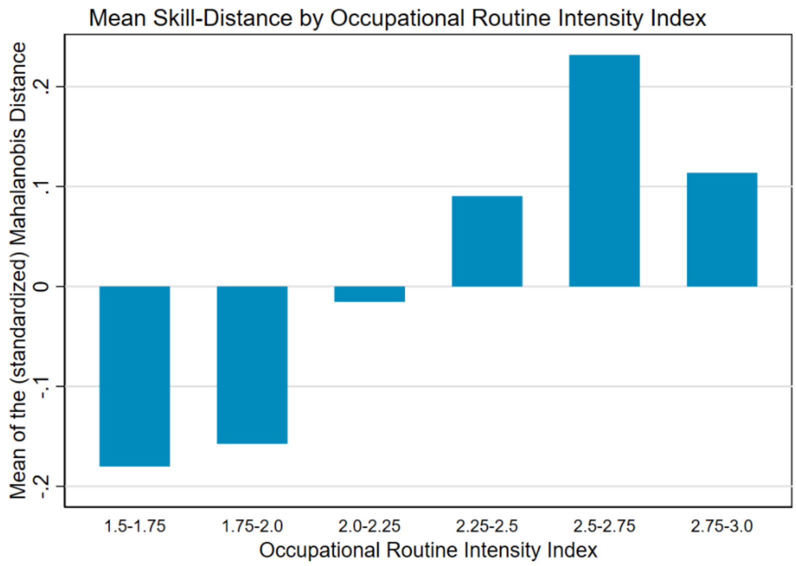

Figure 8 Descriptive relationship between skill specificity and routine tasks

Source: Own calculations based on WeLL data by Institute for Employment Research

Table 1 provides first descriptive information related to the hypotheses by reporting the number of average monthly training hours financed by the employer depending on the level of skill distance and whether the work of the employees is affected by the introduction of new technology or new ICT or software.

Contrary to the H1 hypothesis, employees with high skill distance and thus high skill specificity receive on average less employer-funded training. However, it should be noted that these are only descriptive findings which have not yet been controlled for possible bias. In particular, skill specificity was shown to be related negatively with the ISCO-skill level and positively with routine intensity.

On average, employees facing technological transformation receive more employer-financed further training hours as predicted by H2. The difference between the amount of additional training activities are on average higher for employees with low skill distances (more general skill profiles). This supports the assumption that employers have less incentive to invest in the training of employees with high skill specificity when introducing new technologies, as posited by H3.

Table 1 Average employer-financed monthly training hours

	Low skill distance (SD<= -1)	Medium SD (-1<SD<1)	High SD (SD>=1)
Average employer finances training hours	1.445	1.140	1.134
With new technology	1.709	1.434	1.219
Without new technology	1.400	1.071	1.111
Differences with and without new technology	**0.309**	**0.363**	**0.108**
With new ICT or software	1.937	1.443	1.480
Without new ICT or software	1.335	1.094	1.081
Differences with and without new ICT or software	**0.603**	**0.348**	**0.399**

Source: Own calculations based on WeLL data by Institute for Employment Research

3.3 Regression method and findings

Researchers often chose fixed-effect models to analyse panel data because they control for measured and unmeasured time-variable aspects (level 1 variables). However, fixed-effect models are not capable of providing information on time-constant variables (level 2 variables). Accordingly, current literature points out that a pure consideration of within-effects with the fixed-effects method does not provide enough information and thus may overlook important aspects (Bell et al., 2019). To avoid this, a within-between RE model – also called 'hybrid' model – is used to consider not only within effects but also between effects (following the procedure of Schunck, 2013). When interpreting the between effects, however, it should be considered that these effects are not controlled for (time-constant) unobserved heterogeneity (Bell et al., 2019). The calculated within effects from the within-between RE model are similar to the results of the fixed effects method. To test the robustness of our results we perform a classical fixed effects estimation with robust standard errors in addition to the within-between RE estimation.

The model can be divided into two levels. Level 1 contains the within-estimates and level 2 the between-estimates. In the between estimation it is possible to include fixed and time variable effects in the model and to examine the respective effect sizes. In the within estimation, it is not possible to explicitly include the time-constant variables, though they are controlled for. Accordingly, the exact effect sizes of the time-constant variables cannot be determined in the within estimation but can be revealed in the between estimation. In order to see the differences between people in different occupational groups, the between estimate deliberately refrains from controlling the occupational groups.

The following equation illustrates the REWB model used:

Level 1: Within effects

$$\begin{aligned} Y_{ti} = \beta_{0i} + \beta_{1i} * Skill\ distance_{ti} + \beta_{2i} * New\ technology_{ti} + \beta_{3i} * New\ ICT\&software_{ti} \\ + \beta_{4i} * (New\ technology \times Skill\ distance)_{ti} \\ + \beta_{5i} * (New\ ICT\&Software \times Skill\ distance)_{ti} \\ + \beta_{6i} * ICT\ intensity_{ti} + \beta_{7i} * Working\ hours_{ti} \\ + \beta_{8i} * Wages_{ti} + \beta_{9i} * Routine\ tasks_{ti} \\ + \beta_{10i} * Fixed-term\ contract_{ti} \\ + \beta_{11i} * Job\ status_{ti} \\ + \beta_{12i} * year2007 + \cdots + \beta_{15i} * year2010 + e_{ti} \end{aligned}$$

Level 2: Between effects

$$\begin{aligned} \beta_{0i} = \gamma_{00} + \gamma_{01} * Skill\ distance_{i} + \gamma_{02} * New\ technology_{i} + \gamma_{03} * New\ ICT\&Software_{i} \\ + \gamma_{04} * (New\ technology \times Skill\ distance)_{i} \\ + \gamma_{05} * (New\ ICT\&Software \times Skill\ distance)_{i} \\ + \gamma_{06} * ICT\ intensity_{i} + \gamma_{07} * Working\ hours_{i} \\ + \gamma_{08} * Wages_{i} + \gamma_{09} * Routine\ tasks_{i} \\ + \gamma_{10} * Job\ status_{i} \\ + \gamma_{11} * Fixed-term\ contract_{i} \\ + \gamma_{012} * Western\ German_{i} \\ + \gamma_{013} * Year\ of\ birth_{i} \\ + \gamma_{014} * German\ citizenship_{i} + \gamma_{015} * year2007 + \cdots + \gamma_{018} * year2010 \\ + \gamma_{019} * firm2 + \cdots + \gamma_{0167} * firm149 + u_{0i} \end{aligned}$$

$t = time;\ i = individual$
$\beta_{0i} = intercept;\ \gamma_{00} = constant$
$e_{ti} = error\ term\ that\ varies\ across\ timepoints\ and\ individuals$
$u_{0i} = error\ term\ that\ varies\ across\ individual$

Table 2 shows the estimation results of the model. The estimation was performed for the sample of all respondents in the WELL dataset who participated in all four survey waves (balanced panel). With the exception of the dummy variables and the dependent variable, all variables were included in the model in standardized form. Results are reported separately for within and between effect.

Table 2 Estimates of the REWB-model

DV	Employer-financed training h/month	(1 a) REWB		(1b) REWB		(2) REWB	
Within effects	Skill distance	0.0622*	(0.0363)	0.0747**	(0.0366)	0.1288***	(0.0407)
	New technology	0.5231***	(0.0706)	0.5297***	(0.0706)	0.7120***	(0.0820)
	New ICT/software	0.2414***	(0.0532)	0.2435***	(0.0532)	0.2860***	(0.0614)
	New technology*Skill distance	**-0.2123*** **	(0.0627)	**-0.2101*** **	(0.0627)	**-0.2305*** **	(0.0760)
	New ICT/software*Skill distance	**-0.1144** **	(0.0489)	**-0.1131** **	(0.0489)	**-0.1577*** **	(0.0571)
	ICT intensity						
	ICT intensity 2	0.2720***	(0.1020)	0.2718***	(0.1020)	0.1756	(0.1179)
	ICT intensity 3	0.5570***	(0.1113)	0.5511***	(0.1113)	0.5604***	(0.1270)
	ICT intensity 4	0.4338***	(0.1217)	0.4295***	(0.1217)	0.3714***	(0.1385)
	Working hours	0.1416***	(0.0532)	0.1447***	(0.0532)	0.1596***	(0.0587)
	Routine tasks			-0.1226**	(0.0481)	-0.1401***	(0.0545)
	Job status	✓		✓		✓	
	Fixed-term contract	✓		✓		✓	
	Wages	✓		✓		✓	
	Year dummies	✓		✓		✓	
Between effects	Skill distance	0.0444	(0.1237)	0.0590	(0.1240)	0.0861	(0.1418)
	New technology	0.3164	(0.2355)	0.3885	(0.2400)	0.2528	(0.2923)
	New ICT/software	0.5111***	(0.1956)	0.5267***	(0.1957)	0.8164***	(0.2358)
	New technology*Skill distance	**-0.0771**	(0.2361)	**-0.0846**	(0.2360)	**-0.1082**	(0.2956)
	New ICT/software*Skill distance	**-0.2732**	(0.1968)	**-0.2641**	(0.1968)	**-0.3414**	(0.2369)
	ICT intensity						
	ICT intensity 2	0.2209	(0.2967)	0.1898	(0.2972)	0.2274	(0.3578)
	ICT intensity 3	0.2608	(0.2554)	0.2011	(0.2582)	0.3045	(0.3087)
	ICT intensity 4	0.8242***	(0.2583)	0.7648***	(0.2610)	0.7213**	(0.3129)
	Working hours	0.2013*	(0.1216)	0.2048*	(0.1215)	0.2521*	(0.1407)
	Routine tasks			-0.1451	(0.0945)	-0.1455	(0.1141)
	Job status	✓		✓		✓	
	Fixed-term contract	✓		✓		✓	
	Wages	✓		✓		✓	
	Western Germany	✓		✓		✓	
	German citizenship	✓		✓		✓	
	Firm and Year dummies	✓		✓		✓	
	Constant	-0.0161	(1.3383)	-0.1515	(0.7327)	-0.2534	(1.5328)
	Number of observations	92,431		92,431		76,454	
	Number of groups	1,902		1,902		1,572	
	avg. Obs. per group	48.6		48.6		48.6	
	R-sq-within	0.0020		0.0021		0.0027	
	R-sq-between	0.1393		0.1409		0.1633	
	R-sq-overall	0.0199		0.0202		0.0216	

Source: Own calculations based on WeLL data by Institute for Employment Research
Note: Dependent Variable (DV) = Employer provided training h/month; (2) reduced data sample without employees who do not receive further training due to sufficient qualification; Levels of significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; Standard errors in parentheses; reference category ICT Intensity= "zero or one ICT used"

In Model 1b, the proportion of routine tasks was also included in the model. Though a bias could arise due to the previously established positive correlation between skill distances and routine tasks, the inclusion of the variable "routine tasks" only leads to a slight reduction of the interaction effects, suggesting that the effects are not strongly related to the performance of routine activities. In Model 2, workers were excluded who stated that they have been affected by digitalisation (their work was affected by the introduction of new production techniques, machines or materials, or their equipment of the workplace with information and communication technologies has changed) but they did not receive any training because they constantly learn everything necessary in the current work process and their qualifications are sufficient. The exclusion of these individuals serves as an additional robustness check. The aim is to investigate whether the effects are biased by the fact that employees receive less training not because of skill specificity, but because they are sufficiently qualified. It turns out that excluding the workers changes the relevant effect sizes of the interaction effects only slightly.

The R^2-values of the regression models are very low. However, since the aim of this study is not to predict exact further training hours, but rather a test of the theorized effects, the model is suitable for the study despite the low R^2 value. The following analysis focuses on the results of Model 1b with the more complete set of control variables.

The within regression results show a positive and significant effect of the skill distance on the employer-financed further training hours (0.0747). Employees with higher skill distance thus received more employer-funded training on average. However, the effect size is very small and the effects are turning insignificant when using the fixed effects estimation with robust standard errors (Appendix Table A.4.). The between effects of the skill distance are lower and insignificant (0.0590). Therefore, it can be concluded that the skill distance has only little or even no positive impact on training hours. Accordingly, the H1 hypothesis cannot be confirmed with certainty for the data set used here.

All effects of digitalisation variables (within and between) show positive and large effect sizes on employer-financed training hours. The within effect of introducing new production techniques, machines or materials “new technology” (0.5297) is twice as large as the effect of introducing new ICT or software (0.2435). On the other hand, when looking at the effects *between* individuals, the introduction of new ICT or software leads to almost twice as large an effect (0.5267) on the number of further training courses than the introduction of new technology (0.3885). One reason for this could be that those affected by the introduction of new technologies are more likely to work in jobs that already receive less further training on average. Except for the between effects of new technology, these effect sizes are all statistically significant. The fixed effects estimate with robust standard errors also shows positive and statistically significant effects (Appendix Table A.4). Overall, it can be concluded from these results that being affected by digitalisation (the introduction of new production techniques, machines or materials/the introduction of new ICT or software) leads on average to an increase in monthly employer-financed training hours. H2 can be upheld accordingly.

A closer look at the control variables used also provides interesting information. The results show that people who use more ICT in the workplace received on average significantly more employer-financed training hours. It also reveals that younger employees received more training on average than older employees.

The interaction-effects new technology*skill distance (-0.2101) and new ICT/software*skill distance (-0.1131) show negative and significant within-effects. Both interaction terms have about half as large negative effects as the introduction of the respective techniques. Accordingly, skill specificity appears to have a considerable influence on the amount of continuing training hours when technological transformation takes place. The fixed effects regression with robust standard errors shows only a statistically significant effect for the interaction effect of “New technology*skill distance”. The between interaction effects are not statistically significant but also negative. Overall, many of the between effects are not significant, but the effect sizes are mostly similar to the within effects.

The following figures (9 and 10) illustrate the interaction effects graphically:

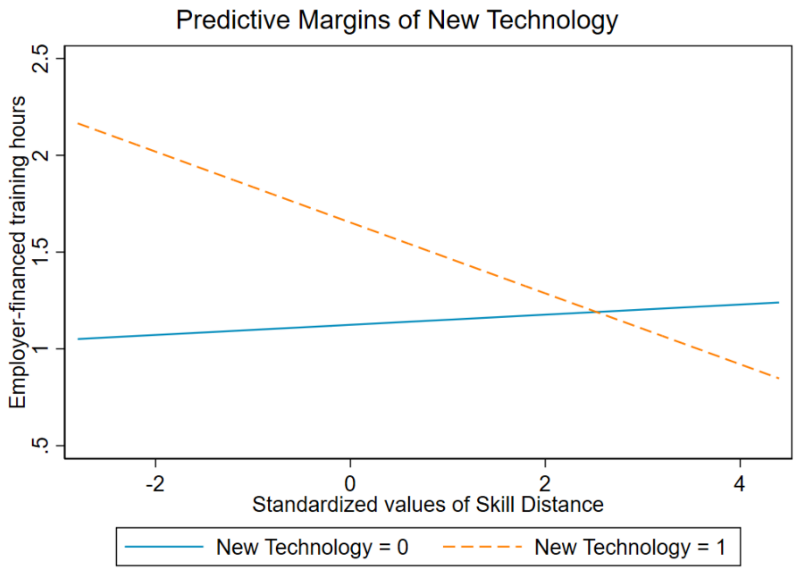

Figure 9 Interaction-effect between "New technology" and "Skill distance" on employer-funded training hours per month

Source: Own calculations based on WeLL data by Institute for Employment Research

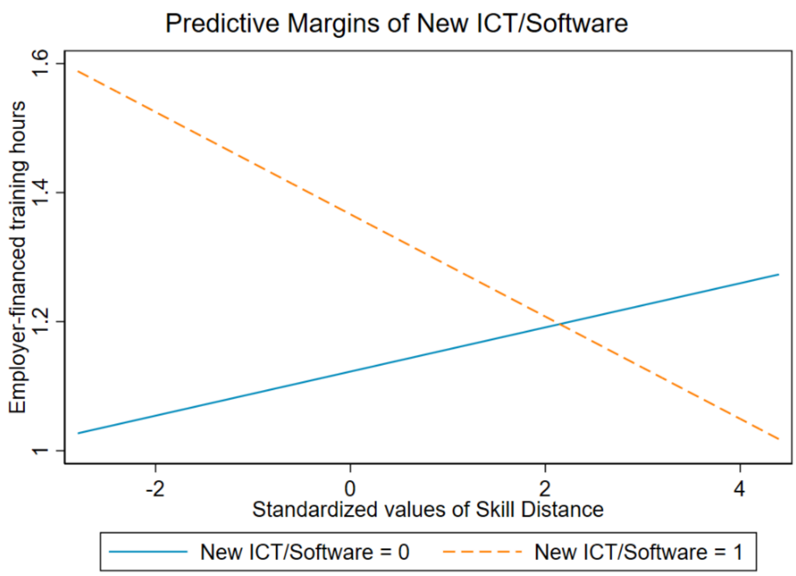

Figure 10 Interaction-effect between "New ICT/Software" and "Skill distance" on employer-funded training hours per month

Source: Own calculations based on WeLL data by Institute for Employment Research

The graphs show that the introduction of the respective technologies leads to an increase in continuing training, but this increase is lower when the skill profiles are more task-specific. In the case of very high skill specificity, the introduction of the technologies even leads to a reduction in the number of average employer-financed further training courses.

A possible explanation for the fact that the interaction effect between the new technology and skill specificity is larger than the interaction effect between skill specificity and new ICT/software is that the two types of technological change may have different effects on workers' bargaining power. Whereas the introduction of new production techniques, machines or materials tends to replace work tasks, new equipment of the workplace with information and communication technologies may have less of a job-replacing effect than a complementary one. Therefore, workers with specific skill profiles will lose more bargaining power and will as a result suffer a reduction in further training more strongly when new production techniques, machines or materials are introduced.

This finding supports H3 according to which employees with specific skill profiles receive less employer-financed further training when they are affected by the introduction of new ICT or software the introduction of new production techniques, machines or materials than employees with more general skill profiles.

3.4 Additional analysis: Labour market situation

Since this effect may be particularly strong if the labour market situation in the employee's industry is poor, an additional calculation was performed to investigate whether this effect is reflected in the data. The calculation involves a three-way interaction between skill specificity, the introduction of ICT/new technology, and the perceived probability of a worsening of the unemployment situation (Item: How likely do you think it is that the unemployment situation in your industry will worsen in the next 12 months?; 0=low probability, 1=high probability). The results show a highly negative significant effect on the receipt of further training if, in addition to a high skill distance, as well as being affected by the introduction of new technologies, the labour market situation is also aggravated. No such effect is found for the introduction of ICT (Appendix Table A.5). These different effects again support the previously stated argument that the introduction of new technologies is probably more often job-threatening. In addition, the two factors skill specificity and the perceived probability of a worsening of the unemployment situation in combination seem to have particularly negative effects on the receipt of training. Accordingly, both factors seem to have a negative effect on bargaining power, which is amplified when both factors are combined.

4 Discussion and conclusion

The results of this study indicate that employees with task-specific skill profiles may be doubly affected by technological change. Existing literature has highlighted that the specificity of skills can become a disadvantage in the context of technological change due to the related lower flexibility and adaptability, and that these disadvantages can be compensated by further training measures (Arntz et al., 2016; Bechichi & Jamet, 2018; Bechichi et al., 2019; Lamo et al., 2011; J. Sanders & Grip, 2004). The results of the analysis indicate that the expected higher training needs for employees with specific skill profiles will probably not be covered by employer-funded training. Although the results of the analysis confirm the assumption of literature that workers on average receive more training in the case of digital change (Gashi et al., 2010; Janssen et al., 2018; Kupets, 2018; Lukowski, 2019; Seyda et al., 2018), this effect is weaker for workers with more task-specific skill profiles compared to those with general skill profiles. The effect is even negative if the qualification profiles are very specific. In other words, they receive less employer-funded training on average in digital change processes than before. These effects can be explained by a shift in bargaining power.

Correspondingly, the study results identify skill specificity as an additional employee characteristic that can lead to cumulative risks in the context of digital transformation, as it leads to lower adaptability and less employer-financed training.

Correlative findings also indicate a possible accumulation of various risk factors. A large body of literature on the skill-biased technological change approach and the task-based approach has identified a low skill level (Bresnahan et al., 2002; O'Mahony et al., 2008) and a high number of routine tasks as possible risk factors for workers (Autor et al., 2003; Frey & Osborne, 2013; Heß et al., 2019; Tamm, 2018; Vries et al., 2020). The analysis results reveal a statistically significant positive correlation between specific skill profiles (low mobility within one's own occupational group) and a high number of routine tasks as well as a low skill level. This correlative relationship indicates cumulative risks for certain groups of workers in times of digital change. Moreover, it may suggest that the task specificity of skill profiles could explain part of the possible loss of bargaining power due to digital transformation, which was previously explained by routine tasks or low skill levels. Therefore, in the future literature on the task-biased and skill-biased technological change approach it would be worthwhile to pay attention to skill specificity, which has so far only been considered very rarely.

The method developed in this paper to measure skill specificity using the Mahalanobis distance can facilitate the consideration of skill specificity in future studies. Until now, the Mahalanobis distance has not been used to determine skill distances or skill specificity. However, it is a very reliable and easy-to-use option (Maesschalck et al., 2000; Mahalanobis, 1936). In particular, its implementation enables the observation of skill distances at the individual level, by taking into account the distribution of the data. This gives it a clear advantage over previously used distance measures. While the Euclidean distance completely ignores the distribution of the data (Poletaev & Robinson, 2008), the angular distance is only appropriate for the observation of two vectors and thus the analysis at occupational level (Bechichi & Jamet, 2018; Bechichi et al., 2019; Eggenberger et al., 2015, 2018; Gathmann & Schönberg, 2010). Accordingly, the development of the new method has been crucial to perform the analysis of skill specificity at the individual level.

The results of this work therefore provide new insights for the flexibility and mobility literature by supplying precise information on the flexibility of workers within their own occupational group. The focus of research for measuring flexibility or mobility so far has been on skill distances between occupational groups due to limited data availability and methodological limitations (Bechichi & Jamet, 2018; Bechichi et al., 2019; Eggenberger et al., 2015; Geel & Backes-Gellner, 2011). For the specific case of German workers, this paper has shown in which occupational groups workers can, on average, more or less easily change to other jobs within their occupational group due to their individual work tasks. In summary, flexibility in low-skilled occupations is significantly lower on average than in high-skilled occupations.

While the results of the analyses are generally robust, there are still some limitations to the research. Since the companies in the WeLL-dataset were not selected randomly, the sample is not representative of German companies and employees. However, the selection criteria are intended to ensure that the results do not reflect any size-, sector- or region-specific characteristics. In addition, the dataset contains detailed information on employees' work tasks, training activities and digitalisation aspects. This information is collected very rarely in one dataset due to the considerable scope of such a study. The fact that the survey was even conducted in panel form is another important advantage. For this reason, the data are nevertheless suitable for the analysis. Future studies should still attempt to use representative data sets that were randomly selected.

Though the information on tasks may be biased by the subjective perceptions of the workers due to self-reporting, it can be assumed that the bias due to social desirability is rather low, since the respondents do not assess their competencies but the frequency of the tasks performed (job requirement approach). Moreover, the analysis could only be considered based on the work tasks queried in the data set. Further studies should verify the results using additional task scales.

Unfortunately, the number of respondents prevents a more detailed examination of individual professions or social groups. Further studies should try to verify the effects found for different groups of people.

The relationship between the number of routine tasks performed, the skill level and the task specificity of the skill profile were shown to be correlative, but should also be examined on a causal level through further research. It could also be investigated whether skill specificity has an impact not only on the receipt of training but also on workers' wages in situations of technological change. The effects of the shift in bargaining could thus become even more apparent.

Though the study has some limitations, it nevertheless provides a number of important practical and public policy implications. Policy makers should consider skill specificity as a potential disadvantage for workers in the course of digital transformation. As employers invest less in the training of employees with task-specific skill profiles in digital change processes despite higher demand, employees cannot enhance their adaptability. It should be noted that a lack of adaptability not only has consequences for the individual employee, but can also have societal and economic consequences such as an increasing rate of unemployment (Lamo et al., 2011; Martins, 2021). The correlative finding that employees with lower skill-level and more routine tasks have, on average, more specific skill profiles may indicate that a lack of training for people with specific skill profiles could in particular increase income inequality and weaken the economy. State-funded training can help to compensate for these disadvantages and enable workers to adapt to changing work requirements. In order to prevent the disadvantage of skill specificity from the beginning, extending initial education and training to a wider variety of work tasks can also improve the situation for younger workers in affected areas (Krueger & Kumar, 2003). Trade unions and workers' representatives can also alter the position of particularly affected groups: they can increase their bargaining power of workers in times of digital change (Haipeter, 2020) or can negotiate directly the provision of further training

(Lammers et al., 2022; Wotschack, 2020). Both employees and their representatives need to be aware of the importance of skill specificity, which is difficult to assess in ongoing employment relationships. Finally, employees with high skill specificity themselves should become active at an early stage to increase their adaptability in order to avoid possible disadvantages due to technological changes.

Funding: This work was supported by the Ministry of Culture and Science of the German State of North Rhine-Westphalia (NRW Forschungskolleg: Design of flexible working environments - human-centered use of Cyber-Physical Systems in industry 4.0; the University of Paderborn).

Acknowledgements: The author is grateful to Prof. Dr. Martin Schneider (Paderborn University) for comprehensive assistance and Prof. Dr. Uschi Backes-Gellner (University of Zürich) and Dr. Christian Eggenberger (University of Zürich) for helpful discussions and advice

Note: The data basis of this paper is the practically anonymised data of the panel "WeLL" –Employee Survey for the project "Further Training as a Part of Lifelong Learning", waves 1-4. The data were accessed via a scientific use file provided by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB). (Project number: 102188). For further information on the dataset see Huber et al. (2011) or Bender et al. (2008).

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Appendix 3

Table A 1 Variables

ICT Intensity	Which of the following information and communication technologies do you use in your job? -computer, internet, mobile phone, e-mail (0) no ICT used (1) one ICT used (2) two ICT used (3) three ICT used (4) four ICT used
New technology	Has your work situation changed due to operational conditions? Has your work been affected by the introduction of new production techniques, machines, materials? (0/1)
New ICT or software	Has the equipment of your workplace with information and communication technologies changed or do you use new software? (0/1)
Employer-financed Training	Who bore the costs of this continuing training measure? Were expenses borne by the employer? (named/ not named)
Training hours	How many (teaching) hours did/does the further training include in total? / How many (teaching) hours did you participate in before you dropped out of further training? (numerically)

Source: Own calculations based on WeLL data by Institute for Employment Research

Table A 2 Skill Categories

I will now list some selected activities. Please indicate how often (possible answers: frequently (2), rarely (1), never (0), don't know) these activities occur in your work.	Task category
Fabricating and producing goods Supervising and controlling machines	Routine manual
Nursing, serving and healing Repairing, patching	Non-routine manual
Gathering information and investigating Developing and researching	Non-routine analytic
Measuring, controlling and quality checks	Routine cognitive
Buying, providing and selling Informing and advising Organizing and planning Negotiating Training, teaching and educating	Non-routine interactive

Source: Tamm (2018)

Table A 3 Allocation of ISCO-88 one-digit Occupation Category to ISCO-Skill-levels

ISCO-Skills-Level	Occupation	Number of respondents	Mean value of the standardized skill distance within the occupation	Mean monthly employer-financed training hours
Skill-Level 1	• Elementary occupations	248	-0.0037	0.3674
Skill-Level 2	• Clerks • Service workers and shop and market sales workers • Skill agricultural and fishery workers • Craft and related worker • Plant and machine operators and assembler	1074	0.1390	0.7810
Skill-Level 3	• Technicians and associate professionals	1071	-0.0161	1.3551
Skill-Level 4	• Professionals	419	-0.1563	1.7090
others	• Legislators, senior-officials and manager	357	-0.1804	

ISCO-88 one-digit occupation category	Number of respondents	Mean value of the standardized skill distance within the occupation	Mean monthly employer-financed training hours
Legislators, senior officials and managers	357	-0.1804	1.54
Professionals	419	-0.1583	1.72
Technicians and associate professionals	1071	-0.0150	1.36
Clerks	210	-0.0340	0.99
Service workers and shop and market sales workers	104	0.2307	0.92
Skilled agricultural and fishery workers	4	0.9497	0.12
Craft and related trades workers	494	0.1414	0.83
Plant and machine operators and assemblers	262	0.2202	0.46
Elementary occupations	248	-0.0042	0.37
Works and staff councils	8	-0.1022	3.64

Source: Own calculations based on WeLL data by Institute for Employment Research

Table A 4 Fixed Effects Regression

Dependent Variable	**Employer-financed training h/month**	**(1) FE (robust SE)**		**(2) FE (robust SE)**	
Within effects	Skill distance	0.0747	(0.0621)	0.1289*	(0.0692)
	New technology	0.5283***	(0.1915)	0.7098**	(0.2357)
	New ICT/software	0.2436**	(0.1003)	0.2863*	(0.1166)
	New technology * Skill distance	**-0.2092***	**(0.1199)**	**-0.2290**	**(0.1437)**
	New ICT/Software * Skill distance	**-0.1134**	**(0.1003)**	**-0.1581**	**(0.1257)**
	ICT intensity (Reference = 0 or 1 ICT used)				
	ICT intensity 2	0.2715	(0.1898)	0.1752	(0.2027)
	ICT intensity 3	0.5508***	(0.1492)	0.5599***	(0.1670)
	ICT intensity 4	0.4292**	(0.1735)	0.3708*	(0.1922)
	Working hours	0.11447**	(0.0682)	0.1596**	(0.0770)
	Routine tasks	-0.1229	(0.0827)	-0.1495	(0.0964)
	Wages	✓		✓	
	Job status	✓		✓	
	Fixed-term contract	✓		✓	
	Year dummies	✓		✓	
	Constant	0.7673	(1.2094)	-0.4764	(0.8343)
	Number of observations	92,569		76,520	
	Number of groups	1,904		1,574	
	Avg. Obs. per group	48.6		48.6	
	R-sq-within	0.0021		0.0027	
	R-sq-between	0.0094		0.0073	
	R-sq-overall	0.0026		0.0031	

Source: Own calculations based on WeLL data by Institute for Employment Research

Note: (2) Reduced data sample without employees who do not receive further training due to sufficient qualification; Levels of significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; Standard errors in parentheses; reference category ICT Intensity= zero or one ICT used

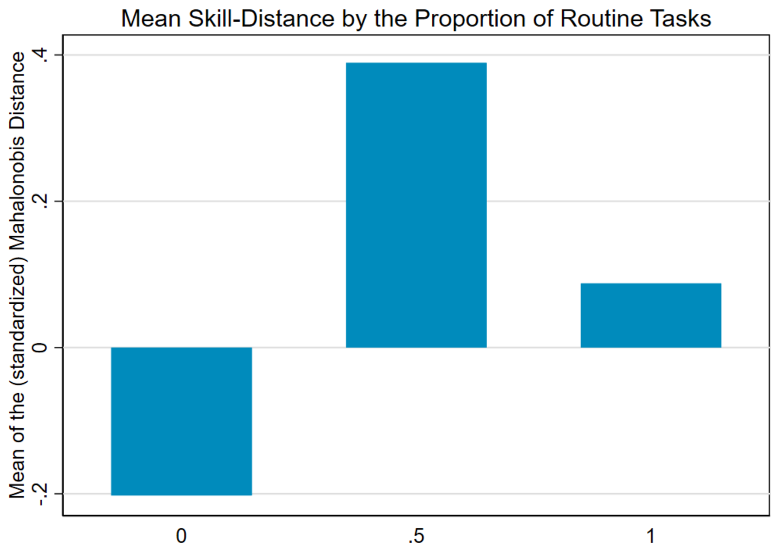

Figure A.1 Relationship between skill distance and the number of routine activities

Source: Own calculations based on WeLL data by Institute for Employment Research

Note: 0 = no routine activity, 0.5 one of two routine activities ("Fabricating and producing goods" or "Supervising and controlling machines"), 1=two routine activities ("Fabricating and producing goods" and "Supervising and controlling machines")

Table A 5 Interaction with Labour market situation

	Employer-financed training h/month	(1) FE (robust SE)		(2) FE (robust SE)		(3) FE (robust SE)	
DV							
Within effects	Skill distance	0.008	(0.065)	0.099	(0.076)	0.039	(0.081)
	New technology	0.695***	(0.239)	0.702***	(0.239)	0.768***	(0.287)
	New ICT/software	0.284**	(0.121)	0.261*	(0.142)	0.286**	(0.120)
	Labour market situation	-0.063	(0.114)	-0.080	(0.122)	-0.015	(0.125)
	Labour market situation * Skill distance			-0.065	(0.108)	0.033	(0.110)
	New technology * Skill distance					-0.114	(0.175)
	New technology * Labour market situation					-0.274	(0.332)
	New technology * Skill distance * Labour market situation					**-0.505***	**(0.292)**
	New ICT/Software * Skill distance			-0.205	(0.147)		
	New ICT/Software * Labour market situation			0.045	(0.221)		
	New technology * Skill distance* Labour market situation			**0.036**	(0.247)		
	ICT intensity (Reference = 0 or 1 ICT used)						
	ICT intensity 2	0.150	(0.213)	0.145	(0.214)	0.138	(0.215)
	ICT intensity 3	0.561***	(0.175)	0.560***	(0.176)	0.547***	(0.175)
	ICT intensity 4	0.384*	(0.199)	0.384*	(0.199)	0.369*	(0.198)
	Working hours	0.156*	(0.083)	0.155*	(0.083)	0.155*	(0.083)
	Routine tasks	-0.138	(0.101)	-0.132	(0.102)	-0.129	(0.100)
	Wages			✓		✓	
	Job status			✓		✓	
	Fixed-term contract			✓		✓	
	Year dummies			✓		✓	
	Constant	0.183	(0.795)	0.081	(0.790)	0.192	(0.806)
	Number of observations	73,948		73,948		73,948	
	Number of groups	1,569		1,569		1,569	
	Avg. Obs. per group	47.1		47.1		47.1	
	R-sq-within	0.0022		0.0024		0.0025	
	R-sq-between	0.0066		0.0085		0.0055	
	R-sq-overall	0.0027		0.0032		0.0027	

Source: Own calculations based on WeLL data by Institute for Employment Research

Note: Reduced data sample without employees who do not receive further training due to sufficient qualification; Levels of significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; Standard errors in parentheses; reference category ICT Intensity= zero or one ICT used. Labour market situation: How likely do you think it is that the unemployment situation in your industry will worsen in the next 12 months? (1=very likely/ rather likely; 0=rather unlikely/very unlikely)