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# “Digital Taylorism” for some, “digital self-determination” for others? Inequality in job autonomy across different task domains

# „Digitaler Taylorismus“ für einige, „digitale Selbstbestimmung“ für die anderen? Ungleichheit der Autonomie in unterschiedlichen Tätigkeitsdomänen

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**Abstract:** In interdisciplinary debates, it is often assumed that changes in job autonomy in the course of digitalisation will be similar for all employees, even across task domains. Some authors postulate the emergence of a “digital Taylorism”, while others suggest that the digital transformation enables more “digital self-determination”. Based on a large-scale survey of employees in Germany, this article quantitatively examines both assumptions, with a particular focus on possible differences across job tasks. The results point to a systematic inequality between the task domains considered: Knowledge-related tasks seem to be associated with increased “digital self-determination”, while the results for manufacturing and service tasks tend towards a pattern of “digital Taylorism”. Overall, the debate needs to go beyond discussing possible future scenarios and address the complex links between job quality, digital technologies and tasks that are already changing the world of work today.

**Keywords:** digital Taylorism, digitalisation, job autonomy, inequality, polarisation, self-determination, task domains

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**Zusammenfassung:** In interdisziplinären Debatten wird häufig davon ausgegangen, dass Veränderungen der Arbeitsautonomie im Zuge der Digitalisierung für alle Beschäftigten ähnlich ausfallen, auch über Tätigkeiten hinweg. Einige postulieren die Entstehung eines „digitalen Taylorismus", während andere davon ausgehen, dass die digitale Transformation mehr „digitale Selbstbestimmung" ermöglicht. Auf der Grundlage einer groß angelegten deutschen Beschäftigtenbefragung werden in diesem Artikel beide Annahmen quantitativ untersucht, wobei ein besonderer Fokus auf möglichen Unterschieden zwischen Tätigkeiten gelegt wird. Die Ergebnisse deuten auf systematische Ungleichheiten zwischen den betrachteten Tätigkeitsdomänen hin: Wissensbezogene Tätigkeiten scheinen mit erhöhter „digitaler Selbstbestimmung" verbunden zu sein, während die Ergebnisse für Produktions- und Dienstleistungstätigkeiten zu einem Muster des „digitalen Taylorismus" tendieren. Insgesamt sollte die Debatte über die Diskussion möglicher Zukunftsszenarien hinausgehen und sich mit den komplexen Zusammenhängen zwischen Arbeitsqualität, digitalen Technologien und Tätigkeiten befassen, die die Arbeitswelt bereits heute verändern.

**Schlagwörter:** Digitaler Taylorismus, Digitalisierung, Autonomie, Ungleichheiten, Polarisierung, Selbstbestimmung, Tätigkeiten

# 1 Introduction

Current debates on the relevance of digitalisation for the world of work are largely dominated by predictions of imminent job losses due to digital technology (Frey/Osborne 2013). The debate is also characterised by buzzwords and specific concepts such as Industry 4.0 or Artificial Intelligence (AI). These predictions and concepts describe a medium- to long-term vision of the future, expecting revolutionary changes.

Given these potentially far-reaching shifts in the labour market, working environments and society as a whole, many would agree that the digital transformation is also a social policy issue. While expected job losses and skill shifts may have implications for social security systems and require labour market policies, it is often overlooked that working conditions are already changing as a result of the increasing use of digital technology. Behind the grandiose public debates about possible digital futures, an ongoing process is already reshaping the working conditions of many employees. This has implications for social policy since the positive and the negative outcomes may affect labour market participation as well as job quality for many, and thus systematically increase or decrease inequalities in the way people perform and experience their work.

In terms of empirical research, neither the relevance of the digital transformation for employees and, in particular, their working conditions nor the possible consequences for their long-term labour market participation have been systematically examined on a large scale. However, some studies already point to changing job quality in the context of digital transformation (Dengler/Tisch 2020; European Commission 2016). One controversial aspect is the impact of digital transformation on job autonomy (Bisht et al. 2021; Gerten et al. 2019; Mazmanian et al. 2013; Parker/Grote, 2020). Some authors suggest that digital technologies will lead to the emergence of so-called "digital Taylorism", systematically reducing autonomy at work. Others, however, argue that digital technologies systematically increase autonomy and thus enable "digital self-determination" at work. While the debate tends to treat the relationship between digital technology and autonomy as a simple either/or question, differentiated and quantitative research that considers the occupation- or task-specific use of digital technology is rare.

In recent years, many different job tasks have increasingly been performed using digital technologies. Thus, digital technologies have been widely introduced into the world of work, although the way in which they are implemented likely varies across job tasks. While the concept of tasks is not uniformly defined across different fields of research, certain task domains, such as knowledge work, manufacturing, service or interactive work, appear in many areas of labour-related research (for a discussion see Autor et al. 2003; Böhle/Glaser 2006; MacDonald/Korczynski 2009; Spitz-Oener 2006). Increasingly, task-specific influences of digital technology are also being taken into account. This is particularly relevant as, for instance, a computer is used differently depending on whether it is used for knowledge work, manufacturing or simple services.

Although the link between job tasks and digital technology is already considered in some influential economic approaches (notably the TASK approach, see Autor et al. 2003), potential changes in job quality are hardly considered. Instead, more attention is paid to the interaction between job tasks and technology in terms of future job losses. Here, the occupation-specific probability of job loss is predicted by the composition of different tasks within occupations, distinguishing for example between (non-)routine and (non-)cognitive tasks. However, technologies and related job tasks are changing, in some cases substantially (Dengler/Matthes 2018). Moreover, the dominant debate about future job losses ignores the fact that digital technology is already systematically changing employees' job quality. So far, however, this has only been researched selectively, often looking at a very specific technology.

One of the main reasons for the lack of comprehensive and generalisable findings is the limited diffusion of new digital technologies, such as various wearables or AI applications. Many of the currently discussed examples are still under develop-ment and their implementation in practice is often limited to a few pioneers. Accordingly, empirical evidence based on large, representative studies is rare. If we abstract from the digital technologies that are currently being intensively discussed but rarely used, it quickly becomes clear that the digital world of work is already in full swing. This is particularly true for computer work, which is currently the most widespread form of digital work and is therefore found in many different occupations. While this technology may seem outdated to some in the current debate, the computer as a general purpose technology (Bresnahan 2010; Helpman 1998) is widely used and therefore allows differences between particular task groups to be studied in a way that is not possible with new but rarely or very specifically used technologies.

Previous studies looking at computer work suggest that digital technologies are generally associated with increased autonomy. These studies mainly focus on an overall correlation between certain technologies (e. g. professional computer or Internet use) and employees' job quality, including job autonomy (e. g. Kirchner 2015; Martin/Omrani 2015). Potential differences between specific subgroups, such as different industries, task domains or educational groups, have been largely ignored. However, it can be assumed that it is the concrete application of technology that affects employees in different task domains to different degrees. Although the computer is an essential part of today's working world in many areas, it can be assumed that the relationship between computer use and autonomy differs systematically in the context of specific task domains. Against this background, the present study contributes to the literature by examining the relationship between computer use and autonomy in different task domains. For this purpose, we discuss perspectives and previous findings, conduct extensive quantitative analyses and develop a unique analytical framework.

## 2 Theoretical considerations

As a basic technology (Bresnahan 2010; Helpman 1998), the computer has become increasingly widespread and is now an essential part of more or less the entire world of work. The varied use of computers in the world of work is based on the fact that computers can be used with a wide variety of software applications in many different task domains. The high and increasing proportion of software and the associated flexible programming of computers enables them to be used for different functions.

The omnipresence of computers raises the question of whether the increasing use of digital technology is systematically accompanied by more or less autonomy for employees. The literature does not yet provide a clear answer to this question.

While some studies point to a gain in autonomy as a result of digital technologies, others point out that computerised job tasks can be better controlled and that digital technology therefore systematically reduces the employee's degree of autonomy. To illustrate these contrasts, two broad theoretical poles of the debate can be distinguished: "digital Taylorism" and "digital self-determination."

## 2.1 "Digital Taylorism" – less autonomy through digital technologies

The debate on the rise of so-called "digital Taylorism" is primarily concerned with the negative consequences of computer-assisted, presumably Taylorist work organisation and assumes a systematic restriction of autonomy. In line with labour process theory (Braverman 1998), the idea of "digital Taylorism" also assumes increasing monitoring by management in highly digitalised workplaces (Gibbs 2017).

Although the term "digital Taylorism" has been used before (e. g. Brown/Lauder/Ashton, 2010), it has gained prominence since 2015, especially through column articles in *The Economist* [1] and *The New York Times* [2] (Holford 2019).[1] Some consider the warehouses of Amazon or Tesco (Moore/Robinson 2016) as a prime example of such "digital Taylorism" and interpret this as the starting point of a general trend. Other prominent examples are crowdsourcing platforms, where an increase in computer-based control of primarily simple job tasks is also suspected (Cherry 2016; Degryse 2017). However, some authors argue that "digital Taylorism" is increasingly affecting cognitive, skilled jobs (Brown et al. 2010). For instance, it has been suggested that knowledge-based tasks can also be codified and routinised by digital technologies (Bain/Taylor 2000; Brown/Lauder 2009), suggesting that technology-induced losses of autonomy are not limited to specific task domains, but rather represent a general trend.

The debate on "digital Taylorism" thus primarily describes specific and mostly negative working conditions. However, the existing contributions provide little or no empirical evidence for a generalisation of this assumption. Moreover, there is hardly any conceptual reference to Taylor's (1911) "principles of scientific manage-

**1** [1] The Economist (2015): "Schumpeter: Digital Taylorism", *The Economist* 12/9/2015, p. 63, or online: http://www.economist.com/news/business/21664190-modern-version-scientific-management-threatens-dehumanise-workplace-digital (accessed: 13/9/2015). [2] NYT (2015): "Inside Amazon: Wrestling Big Ideas in a Bruising Workplace", *The New York Times*, 15/8/2015, http://www.nytimes.com/2015/08/16/technology/inside-amazon-wrestling-big-ideas-in-a-bruising-workplace.html (accessed: 13/9/2015).

ment". Broadly speaking, the pointed assumption is that the use of digital technologies leads to an increase in direct control and concrete guidelines for specific work tasks, and ultimately to a systematic reduction in employee autonomy (for details see Holford 2019).

Some indications of a diffusion dynamic in the sense of a rise of "digital Taylorism" are provided by some empirical case studies in the automotive industry (Butollo et al. 2017) or in the service sector, e. g. in call centres (Bain/Taylor 2000). Others, however, question the assumption that "digital Taylorism" can be interpreted as an independent or even dominant trend towards monitoring employees (Gerten et al. 2019). Studies on crowdsourcing, for example, show higher levels of autonomy and a complex mix of flexibility and control that is not based on Taylorist principles (Wood et al. 2019), leaving the debate with an overall mixed empirical basis for the board claims made.

## 2.2 "Digital self-determination" – more autonomy through digital technologies

Contrary to the position of a "digital Taylorism", the assumption that professional computer use is systematically associated with more decision latitude and thus also with an increased job autonomy can also be found in the literature (Gerten et al. 2019). This position can be interpreted as a counter-thesis that assumes what could be called "digital self-determination" as part of a progressive diffusion of digital technologies. Specifically, some companies seem to combine digital technologies with participative work organisation in order to exploit the potential of digital technologies. This in turn seems to increase autonomy at work (Bresnahan et al. 2002; Brown/Lauder 2009).

Assuming that computers will become more widespread in the world of work, the autonomy of many employees is likely to increase. According to this assumption, employees working with digitally networked technologies will be given greater decision latitude in order to be able to effectively perform new forms of work (e. g. Lindbeck/Snower 2000). At the same time, greater levels of job autonomy are discussed in the context of remote work (Eurofound 2020). However, remote work can be associated with high levels of autonomy but also with adverse job demands such as work intensification or permanent availability – a situation referred to as the autonomy paradox (Gerten et al. 2019; Mazmanian et al. 2013).

Indeed, empirical findings based on available survey data point to a higher decision latitude and autonomy for employees using digital technology at work (Andries et al. 2002; Kirchner 2015; Kraan et al. 2014). Subsequently, these findings generally support the assumption of "digital self-determination" in the course of digitalisation. However, other studies point to differences depending on the type of digital technology (Meyer et al. 2019). Furthermore, most studies based on large survey data examine an overall and thus average correlation. Heterogeneity across groups, e. g. different task domains, may thus remain hidden.

## 2.3 Inequality: digital technology and autonomy across task domains

Comparing the two positions, an incompatible contradiction remains at first sight. Either the increasing use of digital technology is associated with "digital Taylorism", i. e. less job autonomy for employees, or "digital self-determination" with increasing job autonomy. However, this comparison implicitly assumes a uniform underlying trend. Reducing this relationship to an either/or question may not capture potential differences between different groups of employees. It is therefore likely that both sides of the debate are true to some extent, but that neither "digital Taylorism" nor "digital self-determination" are representative of a single trend. One reason for this could be that as digitalisation proceeds, job quality becomes systematically polarised with different employees having opposite levels of decision latitude, even when using the same digital technology in the workplace.

Accordingly, the literature has already pointed out that only a small proportion of employees may potentially benefit from autonomy gains through digital technology. These gains are thought to occur particularly in managerial positions and in knowledge-intensive task domains. In contrast, repetitive tasks that are easy to monitor are associated with reduced autonomy (Jaehrling et al. 2018). The use of digital technologies occurs in a field of tension that enables autonomy, but can also have a restrictive effect. Thus, computer use also carries the risk of increasing inequalities in the world of work. Yet, it is unclear whether this theoretical inequality is also empirically evident.

A starting point for identifying potential differences in the use of digital technology is to consider different task domains separately. A number of task-specific propositions can be found in the extensive debates on the transformation of work (Bell 1973; Kerr et al. 1960; Warhurst et al. 2012). In most cases, specific individual tasks are grouped into broader categories.

The differentiation of task domains is appropriate because in many occupations, tasks are changing due to technology use (Dengler/Matthes 2018). Thus, depending on the level of technology use, tasks within the same occupational domain may differ immensely. Therefore, increasing heterogeneity of different tasks within occupations can be assumed. Examining differences at the level of occupations might underestimate systematic shifts in tasks within and between occupations that occur with the use of digital technology.

In the following, we distinguish different task domains according to previous approaches. The approach taken by Autor, Levy and Murnane (2003), who define task domains as a unit of work activities, is most prominent in the debate on the digital transformation. They argue that the distinction between tasks (and skills) facilitates the analysis of the influence of technological advances on the division of labour between humans and machines. Different domains can be distinguished in terms of the subject matter of the work, i. e. whether the focus is on producing goods, interacting with people (service tasks), or processing information or knowledge (Rösler et al. 2022). The research questions for the empirical analyses conducted in this paper are derived in accordance with this framework. In order to keep the interpretations of the results open, we formulate the expected relationships only for the task domain *knowledge*, while other task domains can be considered accordingly. The assumption of a universal relationship, independent of task domains, serves as the null hypothesis:

*Hypothesis 0a:* *The use of digital technology is associated with a lower level of autonomy, independent of the task domain (universal relationship: "digital Taylorism").*

*Hypothesis 0b:* *The use of digital technology is associated with a higher level of autonomy, independent of the task domain (universal relationship: "digital self-determination").*

However, based on the theoretical considerations, we expect heterogeneous relationships between autonomy and digital technology across task domains and therefore hypothesise the following:

*Hypothesis 1:* *The use of digital technology is associated with higher levels of autonomy the more tasks are permeated by knowledge work (differentiated relationship: "digital self-determination" for knowledge work).*

*Hypothesis 2:* *In other task domains, the use of digital technology is associated with a lower level of autonomy (differentiated relationship: "digital Taylorism" for employees outside the task domain knowledge).*

Hypotheses 1 and 2 assume that the relationship between digital technology and autonomy is moderated by the respective task domain (see Figure 1), i. e. the relationship may differ depending on how pronounced a particular task domain is (B – Moderation). In contrast, hypotheses 0a and 0b assume a universal relationship between digital technology and autonomy (A – Direct).

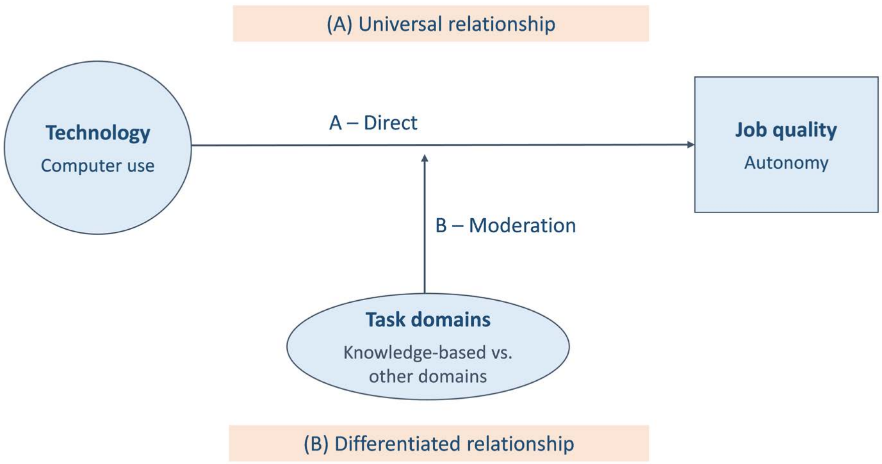


**Figure 1:** Conceptual framework, relationship between digital technology and job quality

Note: Own presentation.

# 3 Data and Variables

The analyses are based on the BIBB/BAuA Employment Survey 2018, a representative cross-sectional survey on qualifications and working conditions in Germany (Gensicke/Tschersich 2018). The survey is conducted every six years and covers approximately 20,000 employees aged 15 years and older, working at least 10 hours per week. This data set is unique for our analyses, as it contains extensive information on working conditions (including variables on job autonomy as well as occupational use of digital technology approximated by computer use) but also on job tasks. We exclude self-employed and freelance workers[2] and restrict the main analyses to employees with valid information on the relevant variables (N=16,824).

We use two different variables to describe job autonomy. On the one hand, planning and arranging one's own work is used as a positive indicator of job autonomy. On the other hand, a variable indicating the opposite direction (reduced autonomy)

2 We focus on dependent employees because the concept of (limited) autonomy naturally applies to the employer-employee relationship and it is easier to draw conclusions with regard to work design (e. g. through co-determination). Moreover, the self-employed are a very specific and heterogeneous group of workers, especially with regard to the degree of autonomy, which is often particularly high and even a reason for the decision to become self-employed (i. e. selection).

is used, i. e. the extent to which work is prescribed. Both variables were collected on a four-point scale (never, rarely, sometimes, frequently). Since a large proportion of employees report being able to frequently plan/arrange their own work (65 %, see Table 1), we dichotomise the variables into frequently (=1) vs. sometimes/rarely/never (=0).[3]

To approximate digital technology we consider the use of computers at work (never=0, sometimes=1, often=2) as the main predictor. One might be concerned that computer use is a very general measure. However, in its capacity as a basic technology, the computer is already widely used in the world of work across industries, in contrast to many other examples of digital technology. Thus, it is an appropriate measure to explore differences across task domains.[4]

As control variables, we include gender and age (linear) as well as the actual hours worked per week (linear). Since the degree of job autonomy depends strongly on employees' qualifications, eight dummy variables for the level of education and vocational training (based on the ISCED-1997 classification) are also included in the analyses. Additional occupation-related control variables, such as occupational groups, are not included as they are indirectly captured by the task domains. In addition, we assume that different tasks occur to different degrees within an occupation. Table 1 shows the distribution of the relevant variables.

# 4 Empirical approach

To investigate the relationship between digital technology and autonomy, as well as the role of different task domains, we proceed in two steps: First, we empirically identify different task domains through exploratory factor analysis. In a second step, we apply regression models with interaction terms to examine the relationship of interest.

3 As a robustness check, we also estimated regression models treating the dependent variables as continuous variables (never=0, rarely=1, sometimes=2, frequently=3), which yielded comparable results (available upon request).

4 In a further analysis, we replicated the results while additionally controlling for the type of computer application (pure adopter, beyond adoption), leading to similar conclusions (results available upon request).

**Table 1:** Sample statistics

| Variable | % |
|---|---|
| **Job autonomy** | |
| Execution of work is prescribed: Frequently | 26.5 |
| Execution of work is prescribed: Sometimes | 26.3 |
| Execution of work is prescribed: Rarely | 27.3 |
| Execution of work is prescribed: Never | 19.9 |
| Plan/arrange own work: Frequently | 64.6 |
| Plan/arrange own work: Sometimes | 16.6 |
| Plan/arrange own work: Rarely | 9.2 |
| Plan/arrange own work: Never | 9.7 |
| **Digital technology** | |
| Computer use: Frequently | 66.0 |
| Computer use: Sometimes | 15.1 |
| Computer use: Never | 18.9 |
| **Covariates** | |
| Male | 54.0 |
| Female | 46.0 |
| Age: 15–34 | 27.9 |
| Age: 35–54 | 56.4 |
| Age: ≥ 55 | 15.7 |
| Educational level: Low | 6.2 |
| Educational level: Intermediate | 64.8 |
| Educational level: High | 29.0 |
| Working hours/ week: 10–34 h | 22.7 |
| Working hours/ week: 35–39 h | 15.4 |
| Working hours/ week: 40–47 h | 47.8 |
| Working hours/ week: ≥48 h | 14.1 |
| N | 16,824 |

Source: BIBB/BAuA Employment Survey 2018, weighted results.

## 4.1 Step 1: Identifying task domains using exploratory factor analysis

The classification of the task domains is determined empirically, as it is not directly available in the data set. This means that the division of the basic task domains discussed above is empirically verified and not just conceptually assumed. Specifically, we build on and extend the analyses conducted by Rohrbach-Schmidt and Tiemann (2013). In doing so, different job tasks are collapsed and compared with the theoretical considerations, thus allowing statements on a broader range of tasks.

Thirteen task items are used to empirically determine the theoretically assumed task domains.[5] Employees were asked how often certain job tasks occur in their work, i. e. frequently, sometimes or never. Based on the 13 selected variables, we apply a polychoric factor analysis with a maximum likelihood estimation, taking into account the ordinal scaled nature of the variables (Kolenikov/Angeles 2004). Since we assume that the tasks are not mutually exclusive, but also occur in combination, a promax rotation method is chosen that allows for overlapping factors.

Three factors are robustly identified by factor analysis (Table 2). The parameters (alpha value and variance) indicate a robust factor solution: The tasks of organising, developing, training, gathering information and advising load on one factor that can be interpreted as the task domain *knowledge*. Manual tasks, such as manufacturing, measuring, monitoring or repairing, load on another factor, that can be interpreted as the task domain *manufacturing*. A third domain can be interpreted as *services*, where tasks such as accommodating, nursing, guarding or cleaning are statistically relevant. For the following analyses, the scores of the three factors are normalised to a range between 0 and 1 for better comparability and interpretation and finally stored as (continuous) variables. Hence, the values describe how pronounced a certain task domain is.

In the factor analysis, we proceeded step by step to find the optimal solution. Thus, in the final factor solution, three task items (transporting, purchasing, and advertising) are excluded, because their factor loadings were inconclusive. These three task items are included as separate (control) variables interacting with computer use in the analyses as smaller task domains (see Table A2 in the Appendix). In the following, we will focus on the larger extracted task domains *knowledge, manufacturing* and *services*.[6]

In various additional analyses, the factor solution with the three identified factors (task domains) was consistently determined. For instance, the results are constant over time and remain robust when calculated on the basis of the analytical sample (N=16,824) or when a principal component analysis is applied.[7] Finally, there is a high degree of content-related and empirical agreement with various other empirical and theoretical task classifications (e. g. Rohrbach-Schmidt/Tiemann 2013). Accordingly, we interpret this factor solution as content reliable and statistically robust.

5 The order of the tasks is randomised within the survey. The computer and Internet use variables were not included in the factor analysis because they are the main predictor in the analyses.

6 As the internal consistency of the three items is rather low (Cronbach's alpha < 0.5) we decided to not include these tasks as an additional factor.

7 Results are available upon request.

**Table 2:** Results of the polychoric factor analysis and the extracted task domains

| | Variable | Factor2 | Factor1 | Factor3 |
|---|---|---|---|---|
| | | *Knowledge* | *Manufacturing* | *Services* |
| 1 | Manufacturing | −0.1632 | 0.7134 | −0.0304 |
| 2 | Measuring | 0.2598 | 0.6885 | −0.0127 |
| 3 | Monitoring | −0.026 | 0.7684 | 0.0211 |
| 4 | Repairing | −0.0941 | 0.6793 | 0.1293 |
| 5 | Organising | 0.5602 | 0.1561 | 0.0083 |
| 6 | Developing | 0.5391 | 0.3651 | −0.2374 |
| 7 | Training | 0.5739 | 0.0121 | 0.2049 |
| 8 | Gathering information | 0.7653 | −0.0795 | −0.0583 |
| 9 | Advising | 0.6758 | −0.2045 | 0.1051 |
| 10 | Accommodating | 0.0572 | −0.0627 | 0.7282 |
| 11 | Nursing | 0.2843 | −0.1037 | 0.7508 |
| 12 | Guarding | 0.1875 | 0.2629 | 0.4363 |
| 13 | Cleaning | −0.3483 | 0.3673 | 0.7276 |
| | **Parameter** | | | |
| | Variance | 2.4324 | 2.3000 | 2.3293 |
| | Cronbach's alpha | 0.6570 | 0.6734 | 0.6407 |

Notes: N=19,881; factor solution, promax rotation, factor loadings < 0.3 shown in grey; calculated by excluding three variables (transporting, purchasing and advertising). Source: BIBB/BAuA Employment Survey 2018, unweighted results.

The extracted task domains *knowledge, manufacturing* and *services* thus each consist of different individual job tasks. The job tasks of each task domain are systematically combined at specific workplaces. For instance, employees who manufacture products also frequently perform other tasks, such as measuring, monitoring and repairing. In terms of the factor analysis presented, these employees are assigned to the domain *manufacturing*. The three domains or factors thus represent the systematic bundling of individual job tasks. These considerations are at least implicitly reflected in the theoretical debate, when speaking of "knowledge work" in contrast to, for example, "manufacturing". In terms of their empirical solution, the factors describe a continuum from low to high values. Accordingly, the factors can be interpreted as follows: The higher the factor, the more the considered job is located at the core of the respective task domain. Thus, the closer a job is to the core of the domain, the more typical the job appears to be for the specific task domain.

Figure 2 shows the average values of the extracted factors for selected occupations. In occupations such as "engineers/chemists/physicists" or in "social/educational professions" the task domain *knowledge* is strongly pronounced, whereas

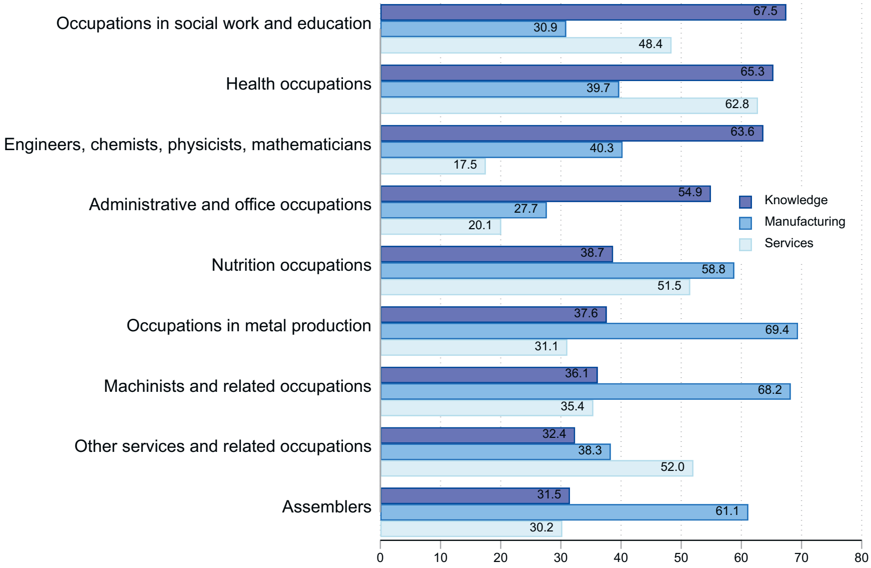


**Figure 2:** Task domains across selected occupations

Notes: Own classification based on the German Classifiaction of Occupations (KldB) 1992[8], only occupations with N ≥ 50 are presented; some occupational titles are abbreviated. Source: BIBB/BAuA Employment Survey 2018, weighted results.

the occupation of "machine operators" or "professions in metal production" are predominantly characterised by the task domain "manufacturing". The differences between occupations are less pronounced for the factor *services*, although the values are particularly high for "health professions". This suggests that the task domain *services* plays a proportionate role in many occupations.[9] Overall, the results presented in Figure 2 support the previous considerations that occupations often involve a number of different tasks and can thus be characterised by a specific combination of different task domains. In particular, the clear assignment of the factors to specific occupations underscores the solidity of the extracted factor solution.

8 https://www.destatis.de/DE/Methoden/Klassifikationen/Berufe/klassifikation-kldb-1992-4st.pdf?__blob=publicationFile

9 This finding is in accordance with the concept of a "service society", in which work is increasingly determined by service-related tasks.

### 4.2 Step 2: Examining the relationship between digital technology and autonomy

To empirically assess the relationship between digital technology and autonomy, we estimate linear Ordinary Least Squares Regression (OLS) with interaction terms. The autonomy variables are treated as dependent variables while computer use, the task domains and their interaction are included as predictors.[10] Since we are using dichotomous variables as dependent variables, we are estimating linear probability models. One might object that the categorical scale of the dependent autonomy variables violates the requirements of a linear regression and that a nonlinear regression model seems appropriate. However, the interpretation of interaction terms in nonlinear regressions is quite complex (e. g. Ai/Norton 2003; Greene/Hensher 2010), and often complex (ordinal) logistic regression models do not meet basic statistical requirements. Therefore, the estimation of linear OLS models is preferred to make the analyses more comprehensive. In addition, heteroscedasticity-robust standard errors are computed.

Due to the cross-sectional nature of the data and the empirical approach chosen, the analyses do not allow causal interpretations. Thus, the analyses only determine the simultaneous, systematic occurrence of the variables examined.

## 5 Results

The following analyses examine whether the relationship between digital technology and autonomy differs across task domains by estimating interaction models. The results are presented in Table 3, where the interaction terms can be interpreted as follows: A positive interaction effect indicates a strengthening of the relationship between the degree of computer use and autonomy, the more the respondent's job is characterised by the respective task domain. A negative interaction effect indicates a weakening of this relationship as the task domain becomes more pronounced. For the sake of illustration, we have plotted the results graphically (Figure 3). Since autonomy is considered with two single items, separate models are estimated. Model 1 (left column) shows the results for the dependent variable "Execution of work is prescribed in detail" and Model 2 (right column) shows the results for the dependent variable "Plan/arrange own work". The results reported in each column

**10** Interaction terms are included linearly in the analyses. In further analyses, quadratic interactions were also estimated to identify nonlinear relationships (cf. Mitchell 2012) with similar results (results available upon request).

are part of the same regression model, but are presented separately for each task domain for clarity.

We calculated marginal effects for ease of interpretation. Thus, the figures illustrate the predicted values of the autonomy variables for different values of the task domains and their corresponding confidence interval according to the extent of computer use at work (never, sometimes, often). The red line shows the average autonomy scores for frequent computer users and the blue line for employees who never use a computer at work. For the sake of completeness, the grey line represents the values for employees who report that they sometimes use a computer, although we will not further discuss this category below.[11] Figure 3 thus illustrates differences in autonomy by the frequency of computer use depending on the extent of the respective task domain. In the case of parallel lines, there would be no interaction between the frequency of computer use and the level of the specific task domain. Consequently, we expect a task-specific difference in the relationship when the two lines are not parallel, but differ in their slope, and probably even cross each other (i. e. rise or fall in opposite directions). To interpret the results, we take the (normative) position from the debate: At least in public debates, more autonomy is generally seen as beneficial, while less autonomy is seen as detrimental.[12]

Regardless of the autonomy variable considered, the results indicate some significant differences in computer use across the three task domains. For the task domain *knowledge* (Figure 3, first row), a rather favourable relationship is shown. The higher the factor *knowledge*, the lower the probability that employees with frequent computer use report that their work is prescribed in detail. In contrast, the correlation tends to be the opposite for employees without professional computer use. The results for the other autonomy variable consistently indicate that for employees who use computers, more knowledge-related tasks are associated with a higher probability of planning and arranging their own work.

The picture is less clear for the task domain *manufacturing* (Figure 3, second row). Respondents with high scores for the task domain *manufacturing* benefit from frequent computer use in that they are more likely to plan or arrange their own work than employees without computer use. The relationship for the variable “work is prescribed in detail” also tends to be favourable. Respondents in the task domain *manufacturing* with frequent computer use are less likely to report that their work is prescribed in detail. The relationship is consistently different for

**11** Because a linear model was estimated, the marginal effects of each category of computer use variable lie on a straight line.

**12** However, there is increasing evidence that too much autonomy can also have negative consequences (Kubicek et al. 2017; Väänänen et al. 2020).

**Table 3:** Relationship between computer use, task domain and autonomy (OLS)

| **Dependent Variable** ***(Frequently vs. Sometimes/rarely/never)*** | **Work is prescribed** | **Plan/arrange own work** |
|---|---|---|
| Computer: Never | *Reference* | *Reference* |
| Computer: Sometimes | 0.0107 | −0.0887 |
| | (0.0533) | (0.0557) |
| Computer: Frequently | 0.0199 | 0.2260*** |
| | (0.0398) | (0.0402) |
| Knowledge [0,1] | −0.1084 | 0.1939** |
| | (0.0650) | (0.0712) |
| Computer: Sometimes x Knowledge | −0.2206* | 0.3915*** |
| | (0.0865) | (0.0948) |
| Computer: Frequently x Knowledge | −0.2390*** | 0.3031*** |
| | (0.0703) | (0.0763) |
| Manufacturing [0,1] | 0.0389 | −0.0104 |
| | (0.0565) | (0.0590) |
| Computer: Sometimes x Manufacturing | 0.1898* | 0.0321 |
| | (0.0740) | (0.0792) |
| Computer: Frequently x Manufacturing | 0.0936 | −0.1285* |
| | (0.0596) | (0.0621) |
| Services [0,1] | −0.0729 | 0.2422*** |
| | (0.0564) | (0.0590) |
| Computer: Sometimes x Services | 0.0102 | −0.3181*** |
| | (0.0705) | (0.0776) |
| Computer: Frequently x Services | 0.2338*** | −0.5620*** |
| | (0.0594) | (0.0622) |
| N | 16,824 | 16,824 |
| adj. $R^2$ | 0.0838 | 0.1410 |

Notes: * p<0.05, ** p<0.01, ***p<0.001; robust standard errors in parentheses. Control variables included: gender, age, weekly working hours, eight educational dummies, smaller task domains (purchasing, advertising, transport incl. interaction terms with computer use); see also Figure 2 and Table A2. Source: BIBB/BAuA Employment Survey 2018; unweighted results.

those who never use a computer at work, as their work is more often prescribed. However, compared to the results for the task domain *knowledge*, employees in the task domain *manufacturing* do not benefit from computer use to the same extent.

The results suggest a negative relationship for the task domain *services* (Figure 3, third row). The higher the factor *services*, the more likely respondents with frequent computer use are to report that their work is prescribed in detail. The results for the other autonomy variable are similar: the higher the values for the task domain *services*, the less likely respondents with frequent computer use are to report being able to plan or arrange their own work. This relationship seems to be exactly the opposite for employees without computer use.

With respect to the hypotheses derived above, we conclude the following: The relationships estimated indicate a substantial moderating role of the task domains. Thus, the null hypotheses 0a and 0b can be rejected as there is no empirical evidence for a universal relationship. This applies both to the assumption of "digital Taylorism" and to the assumption of "digital self-determination". The findings clearly indicate that the relationship between autonomy and computer use varies depending on the task domain. The results thus support hypothesis 1, which states that the use of digital technology in the task domain *knowledge* is associated with higher levels of autonomy. Hypothesis 2 is partially supported by the empirical findings. While there are consistently unfavourable correlations for the task domain *services*, the results for the task domain *manufacturing* vary depending on the autonomy variable considered.

Replicating the analyses with earlier waves of the BIBB/BAuA Employment Survey 2006 and 2012 reveals very similar relationships (cf. Table A1 and A2 in the appendix). The fact that the results are constant over time indicates the robustness of the estimated correlations. The results are partly stronger for more recent times, which suggests that the interaction between digital technology and task domains is becoming increasingly relevant with respect to job autonomy.

## 6 Discussion and conclusion

This article represents a first step towards empirically examining the relationship between autonomy and digital technology across different task domains. For the analyses, we derived hypotheses on the relationship between autonomy and digital technology from the literature, with a particular emphasis on investigating differences between the job tasks performed. This assumption contrasts to the more polarised positions in the debate, which either expect a general loss of autonomy, summarised under the broad label "digital Taylorism", or a general gain in autonomy, which could be called "digital self-determination".

Aiming to identify heterogeneous associations, we analytically defined task domains as a bundle of different individual job tasks. An explorative factor analysis identified three task domains: *knowledge*, *manufacturing* and *services*. Building on the analytical framework, the empirical approach explicitly considered job tasks that frequently co-occur. The complex relationships were statistically estimated by OLS regression analysis, including the initially identified task domains as interacting

Model 1 | Model 2

*Job autonomy: Work is prescribed in detail* | *Job autonomy: Plan/arrange own work*

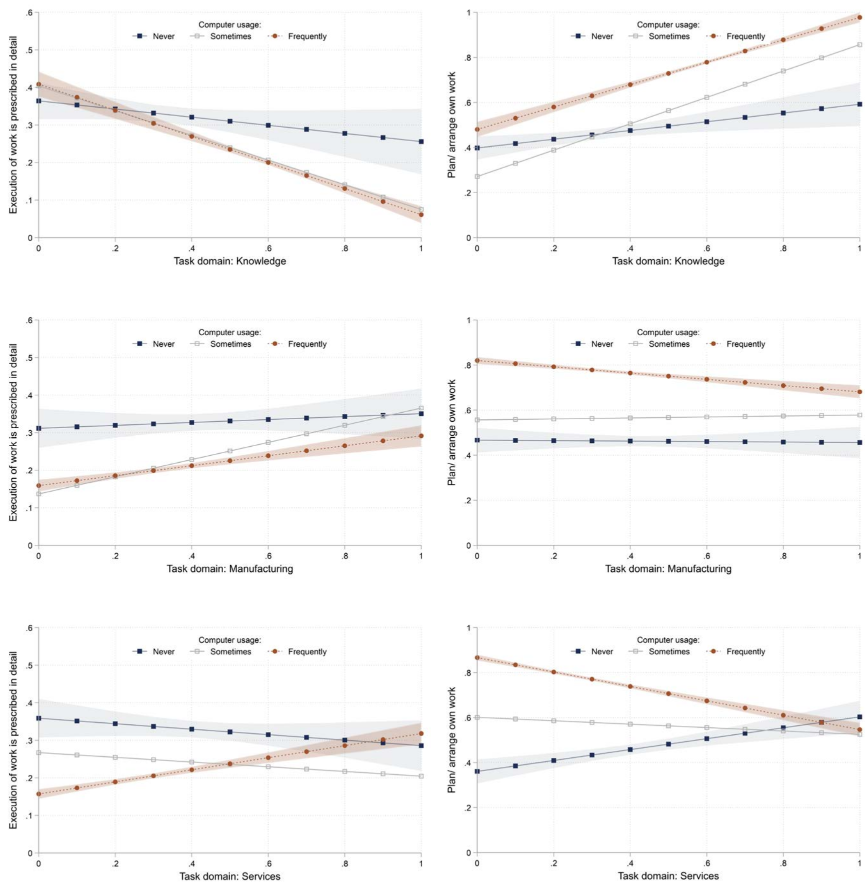


**Figure 3:** Relationship between job autonomy and computer use across task domains (marginal effects)

Notes: Based on OLS regressions with interaction terms (c.task domain x i.computer use, see Table A2 in the Appendix) for the categorical variable computer use; shaded areas represent the respective 95 % confidence interval, N=16,824. Source: BIBB/BAuA Employment Survey 2018, unweighted results.

variables. In this context, the use of computers at work was used as a general indicator for working with digital technology as this is currently the most widespread digital technology, allowing us to examine differences across task domains that would not be possible with new but rarely and very specifically used technologies.

Overall, the empirical findings indicate heterogeneous associations between autonomy and digital technology across the three task domains. The more *knowledge*-related an employee's job tasks are, the greater the systematic benefits of frequent computer use in terms of autonomy. For the task domain *manufacturing*, frequent computer use at work also tends to be beneficial in terms of autonomy, but to a much lesser extent than for the knowledge-related task domain. An opposite picture emerges for the task domain *services*. Here, employees without professional computer use report higher levels of autonomy while it is systematically lower for respondents with frequent computer use. Taken as a whole, the results point to already existing task-specific inequalities in job quality when working with digital technologies.

Our findings contribute to the general debate on the relevance of digitalisation for the world of work. Prominent forecasts predict disruptive changes in the labour market with job losses that could lead to inequalities in the future. However, our results suggest that there is already a systematic inequality in the distribution of job quality in today's world of work. The extent to which this inequality – which predates the recent and ongoing digitalisation process – reinforces existing inequalities or creates new ones, needs to be further explored in future research. In analogy to the private use of digital technologies (c.f. Van Deursen/Van Dijk 2014), this digital divide in the world of work does not seem to exist in the sense that certain groups are excluded from the use of digital technologies per se. Rather, inequalities in job quality can be observed depending on the intensity of use but also on the job task performed. Thus, the process of digitalisation appears to produce considerable inequalities in job quality even before widespread job losses are evident.

In this paper, we also refer to two dominant perspectives that assume that digitalisation is inevitably associated with "digital Taylorism" or "digital self-determination", both of which reflect a common underlying trend. The empirical findings suggest that limiting the debate on the consequences of digitalisation to these two positions seems inaccurate. Moreover, we show that whether the use of digital technologies is associated with "digital Taylorism" or "digital self-determination" depends on the specific task domain. The results also reveal a systematic context dependency, assuming that digital technology itself does not determine its effects. It should be emphasised that the results do not indicate "digital Taylorism" for knowledge-related workplaces. Thus, the assumption that the use of digital technology will lead to a loss of autonomy in knowledge-related job tasks does not seem to hold. On the contrary, the results indicate that the use of digital technology is associated with systematic gains in autonomy for respondents working in the core of the task domain *knowledge*.

When analysing and interpreting the results, some limitations must be kept in mind. First, the relationship between digital technology and autonomy is proxied by the frequency of professional computer use. Given the rapid pace of technological change, there are still some arguments supporting this approach, e. g. its widespread diffusion across task domains. However, future research needs to examine this relationship based on further technological innovations when they are sufficiently widespread to allow heterogeneity analyses across task domains. In addition, tasks that have not yet been digitalised may include tasks that cannot be digitalised at all. In our analyses we cannot distinguish between these two groups of tasks, as they are both executed by respondents who never use a computer at work. However, tasks that cannot be digitalised may be associated with a certain degree of autonomy. Similarly, it could be that workplaces characterised by a higher degree of autonomy (e. g. knowledge-related tasks) are more likely to be equipped with digital technologies in order to exploit the potential for efficiency gains more effectively. In this respect, the causality may be reversed and we cannot rule out that the cross-sectional results are (partly) driven by endogeneity. Thus, the estimated relationships should not be interpreted causally. Future research should take this into account and examine the relationship based on longitudinal data or quasi-experimental methods.

Second, there are other limitations related to the task items within the data set used. Although the items in the BIBB/BAuA Employment Survey are comparatively comprehensive, different tasks are grouped together (e. g. nursing, caring and healing are surveyed in one item). A more differentiated survey of individual job tasks would potentially ensure a better assignment to the different task domains.

Third, the results are not fully generalisable to other contexts. Although we consider two different indicators of autonomy that are relevant for different task domains, we cannot conclude that these correlations hold for all dimensions of (job) autonomy per se. Similarly, our analyses focus on dependent employees, so that the results are not easily transferable to the self-employed. However, this issue is also relevant for the self-employed, e. g. individuals working via platforms. Moreover, the analyses are based on data from Germany only. While Germany is one of the core countries in the debate, the specific institutional background needs to be taken into account (Hauff/Kirchner 2022; Kirchner/Hauff, 2017). Future research should thus examine this relationship for other countries and contexts and also focus on different dimensions of autonomy or flexibility in order to better understand the complex relationships underlying the interactions between autonomy, technology use and task domains.

A final limitation concerns the empirical approach chosen to identify broad task domains through exploratory factor analysis. Although this approach allows us to identify three task domains, with respect to the task domain *services* it fails to distinguish between person-related and object-related services. This distinction is particularly important, since especially the interaction with other people has completely different requirements than working with objects.

In summary, future research on the impact and implications of digitalisation should focus on differences between tasks or dimensions below the occupational level. This is because it can be expected that tasks within occupations will change with the increasing use of digital technology. Conversely, the results indicate that occupations, and thus the everyday working lives of many employees, consist of several different job tasks, including different task domains. However, the extent to which the interaction and relationship between different tasks is relevant remains an open question for future research.

Although this article is only a first step to empirically examining different assumptions in the current debate on the relevance of digitalisation for job quality, some recommendations can be derived. Especially in service-related tasks, but also in manufacturing, the increasing use of computer-based technologies does not seem to be associated with gains in autonomy. Consequently, the extent to which potential losses of autonomy can be compensated by other tasks in order to ensure a humane working environment should be considered. Enriching jobs with knowledge-related tasks could be one possibility, which may also enable a more inclusive design of work. At the same time, the finding that greater levels of autonomy for employees can also involve overload and excessive demands should also be considered. Digital technology that limits autonomy on the one hand and supports work processes from an employee's point of view on the other hand, could be advantageous for some individuals. Finally, it also depends on the specific design of working conditions whether autonomy functions as a resource or whether it is rather perceived as an additional stressor.

The empirical findings suggest that digitalisation processes are already changing working conditions and job quality. The unequal distribution of increased and decreased autonomy across task domains is a major challenge for practitioners and policymakers. From a social policy perspective in particular, changing job quality and systematic inequalities in the digital transformation could jeopardise many of the hard-won improvements in the workplace. This issue could become particularly pressing as declining job quality could increase workplace conflicts and be detrimental to employee health, with potential implications for the labour market and social security systems. Overall, the debate needs to move beyond the grandiose public debate about possible digital futures and address the complex associations between job quality, digital technologies and task domains that are already changing how individuals perform and experience work in an increasingly digitalised world of work.

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# Appendix

**Table A1:** Results of the polychoric factor analysis and the extracted task domains over time

| | Variable | 2018 (N=19,881) | | | 2012 (N=19,885) | | | 2006 (N=19,918) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Factor 1 | Factor 2 | Factor 3 | Factor 1 | Factor 2 | Factor 3 | Factor 1 | Factor 2 | Factor 3 |
| | | ***Knowledge*** | ***Manufa-cturing*** | ***Services*** | ***Knowledge*** | ***Manufa-cturing*** | ***Services*** | ***Knowledge*** | ***Manufa-cturing*** | ***Services*** |
| 1 | Manufacturing | −0.1632 | 0.7134 | −0.0304 | −0.1328 | 0.7485 | −0.0543 | −0.1786 | 0.7320 | −0.0384 |
| 2 | Measuring | 0.2598 | 0.6885 | −0.0127 | 0.2342 | 0.7018 | 0.0008 | 0.2298 | 0.6827 | 0.0437 |
| 3 | Monitoring | −0.0260 | 0.7684 | 0.0211 | −0.0161 | 0.7301 | 0.0404 | −0.0245 | 0.7414 | 0.0453 |
| 4 | Repairing | −0.0941 | 0.6793 | 0.1293 | −0.0652 | 0.6590 | 0.0931 | −0.0663 | 0.6724 | 0.1064 |
| 5 | Organising | 0.5602 | 0.1561 | 0.0083 | 0.5976 | 0.1380 | 0.0135 | 0.5809 | 0.1400 | 0.0135 |
| 6 | Developing | 0.5391 | 0.3651 | −0.2374 | 0.5796 | 0.3528 | −0.2099 | 0.5603 | 0.3679 | −0.2389 |
| 7 | Training | 0.5739 | 0.0121 | 0.2049 | 0.5965 | 0.0419 | 0.1530 | 0.6136 | 0.0360 | 0.1219 |
| 8 | Gathering information | 0.7653 | −0.0795 | −0.0583 | 0.8028 | −0.0890 | −0.0515 | 0.8085 | −0.0733 | −0.1088 |
| 9 | Advising | 0.6758 | −0.2045 | 0.1051 | 0.6672 | −0.1791 | 0.1021 | 0.7091 | −0.1990 | 0.0485 |
| 10 | Accommodating | 0.0572 | −0.0627 | 0.7282 | 0.0612 | −0.0589 | 0.7123 | 0.0730 | −0.1025 | 0.6799 |
| 11 | Nursing | 0.2843 | −0.1037 | 0.7508 | 0.2781 | −0.1300 | 0.7272 | 0.3379 | −0.0976 | 0.6426 |
| 12 | Guarding | 0.1875 | 0.2629 | 0.4363 | 0.1941 | 0.2197 | 0.4381 | 0.2601 | 0.2535 | 0.3643 |
| 13 | Cleaning | −0.3483 | 0.3673 | 0.7276 | −0.3728 | 0.3603 | 0.7117 | −0.3611 | 0.3240 | 0.7441 |
| | **Parameter** | | | | | | | | | |
| | Variance | 2.6997 | 2.4324 | 2.3293 | 2.6141 | 2.6301 | 2.2444 | 2.6935 | 2.6195 | 2.0387 |
| | Cronbach's Alpha | 0.6570 | 0.6734 | 0.6407 | 0,6892 | 0,6774 | 0,6200 | 0.6910 | 0.6818 | 0.5826 |

Note: Factor solution, promax rotation, factor loadings < 0.3 shown in grey; calculated by excluding three variables (transporting, purchasing and advertising). Source: BIBB/BAuA Employment Survey 2006, 2012, 2018, unweighted results.

**Table A2:** Relationship between computer use, task domain and autonomy (OLS) over time

| **Dependent Variable** *(Frequently vs. Sometimes/rarely/never)* | **2006** | | **2012** | | **2018** | |
|---|---|---|---|---|---|---|
| | **Work is prescribed** | **Plan own work** | **Work is prescribed** | **Plan own work** | **Work is prescribed** | **Plan own work** |
| Computer: Never | *Reference* | *Reference* | *Reference* | *Reference* | *Reference* | *Reference* |
| Computer: Sometimes | −0.0619 | −0.0046 | −0.0286 | −0.0893 | 0.0107 | −0.0887 |
| | (0.0400) | (0.0422) | (0.0442) | (0.0463) | (0.0533) | (0.0557) |
| Computer: Frequently | 0.0314 | 0.2611*** | 0.0484 | 0.2246*** | 0.0199 | 0.2260*** |
| | (0.0295) | (0.0296) | (0.0316) | (0.0320) | (0.0398) | (0.0402) |
| Knowledge [0,1] | 0.1746*** | −0.1177* | −0.0512 | 0.3356*** | −0.1084 | 0.1939** |
| | (0.0451) | (0.0459) | (0.0570) | (0.0591) | (0.0650) | (0.0712) |
| Computer: Sometimes x Knowledge | 0.0532 | 0.0331 | −0.1561* | 0.3631*** | −0.2206* | 0.3915*** |
| | (0.0607) | (0.0641) | (0.0783) | (0.0809) | (0.0865) | (0.0948) |
| Computer: Frequently x Knowledge | −0.0269 | −0.0501 | −0.2355*** | 0.2470*** | −0.2390*** | 0.3031*** |
| | (0.0489) | (0.0496) | (0.0629) | (0.0643) | (0.0703) | (0.0763) |
| Manufacturing [0,1] | −0.0554 | 0.4522*** | 0.1080* | 0.0512 | 0.0389 | −0.0104 |
| | (0.0488) | (0.0511) | (0.0487) | (0.0497) | (0.0565) | (0.0590) |
| Computer: Sometimes x Manufacturing | −0.1602* | 0.2168** | 0.1248 | −0.0467 | 0.1898* | 0.0321 |
| | (0.0696) | (0.0725) | (0.0667) | (0.0685) | (0.0740) | (0.0792) |
| Computer: Frequently x Manufacturing | −0.2693*** | 0.0991 | 0.029 | −0.1955*** | 0.0936 | −0.1285* |
| | (0.0553) | (0.0572) | (0.0526) | (0.0532) | (0.0596) | (0.0621) |
| Services [0,1] | −0.0601 | 0.2506*** | −0.0063 | 0.1699*** | −0.0729 | 0.2422*** |
| | (0.0423) | (0.0438) | (0.0471) | (0.0490) | (0.0564) | (0.0590) |
| Computer: Sometimes x Services | 0.0514 | −0.2940*** | 0.0507 | −0.2236** | 0.0102 | −0.3181*** |
| | (0.0595) | (0.0637) | (0.0652) | (0.0685) | (0.0705) | (0.0776) |
| Computer: Frequently x Services | 0.1973*** | −0.5078*** | 0.1354** | −0.4370*** | 0.2338*** | −0.5620*** |
| | (0.0470) | (0.0485) | (0.0511) | (0.0527) | (0.0594) | (0.0622) |
| Purchasing [0,1] | −0.1502*** | 0.0638** | −0.1346*** | 0.0900*** | −0.0509 | 0.0814* |
| | (0.0219) | (0.0240) | (0.0241) | (0.0259) | (0.0317) | (0.0336) |
| Computer: Sometimes x Purchasing | 0.0779* | 0.0725* | −0.0466 | 0.0881* | −0.0441 | 0.0718 |
| | (0.0333) | (0.0357) | (0.0350) | (0.0376) | (0.0421) | (0.0458) |
| Computer: Frequently x Purchasing | 0.0708** | 0.0149 | 0.0423 | −0.028 | −0.0335 | −0.0033 |
| | (0.0240) | (0.0258) | (0.0262) | (0.0276) | (0.0331) | (0.0351) |
| Advertising [0,1] | 0.038 | −0.0325 | −0.0256 | −0.0264 | 0.0935 | −0.0086 |
| | (0.0341) | (0.0349) | (0.0402) | (0.0409) | (0.0496) | (0.0505) |
| Computer: Sometimes x Advertising | −0.0679 | 0.09 | 0.0391 | 0.0029 | −0.0743 | 0.029 |
| | (0.0463) | (0.0489) | (0.0522) | (0.0537) | (0.0605) | (0.0647) |
| Computer: Frequently x Advertising | −0.0731* | 0.0691 | −0.0148 | 0.0307 | −0.1441** | 0.0548 |
| | (0.0357) | (0.0365) | (0.0418) | (0.0423) | (0.0506) | (0.0515) |
| Transport [0,1] | 0.0363 | −0.0148 | 0.0611** | −0.0683** | 0.0322 | −0.0723** |
| | (0.0202) | (0.0207) | (0.0217) | (0.0224) | (0.0258) | (0.0266) |

| Dependent Variable *(Frequently vs. Sometimes/rarely/never)* | 2006 | | 2012 | | 2018 | |
|---|---|---|---|---|---|---|
| | **Work is prescribed** | **Plan own work** | **Work is prescribed** | **Plan own work** | **Work is prescribed** | **Plan own work** |
| Computer: Sometimes x Transport | 0.0527 | 0.008 | 0.0272 | 0.0864* | −0.0264 | 0.0559 |
| | (0.0313) | (0.0326) | (0.0335) | (0.0340) | (0.0369) | (0.0392) |
| Computer: Frequently x Transport | 0.0221 | 0.015 | 0.002 | 0.0690** | 0.0357 | 0.0566 |
| | (0.0231) | (0.0233) | (0.0247) | (0.0249) | (0.0282) | (0.0289) |
| ISCED: 1 Primary education | 0.0341 | −0.1048* | 0.0822 | 0.0125 | 0.0624 | −0.0832 |
| | (0.0503) | (0.0484) | (0.1214) | (0.1178) | (0.1210) | (0.1175) |
| ISCED: 2b Lower secondary | 0.0091 | −0.0579* | 0.0348 | −0.0395 | 0.0362 | −0.0950** |
| | (0.0223) | (0.0231) | (0.0226) | (0.0227) | (0.0305) | (0.0304) |
| ISCED: 2a Lower secondary | 0.0321 | −0.0151 | 0.052 | −0.0778** | −0.0207 | −0.0205 |
| | (0.0268) | (0.0264) | (0.0281) | (0.0275) | (0.0319) | (0.0323) |
| ISCED: 3b Upper secondary | *Reference* | *Reference* | *Reference* | *Reference* | *Reference* | *Reference* |
| ISCED: 3a Upper secondary | −0.0291 | −0.0609* | 0.0254 | 0.0177 | −0.0441 | −0.0401 |
| | (0.0223) | (0.0244) | (0.0303) | (0.0299) | (0.0235) | (0.0255) |
| ISCED: 4a Post secondary | −0.0175 | 0.0290* | −0.0280* | 0.0253* | −0.0725*** | 0.0439*** |
| | (0.0115) | (0.0114) | (0.0125) | (0.0123) | (0.0109) | (0.0116) |
| ISCED: 5b Tertiary education | −0.0582*** | 0.0627*** | −0.0401** | 0.0764*** | −0.0446*** | 0.0572*** |
| | (0.0131) | (0.0129) | (0.0126) | (0.0115) | (0.0126) | (0.0125) |
| ISCED: 5b Tertiary education | −0.1090*** | 0.0557*** | −0.0996*** | 0.0413*** | −0.1181*** | 0.0768*** |
| | (0.0082) | (0.0084) | (0.0087) | (0.0085) | (0.0086) | (0.0089) |
| Female | 0.0316*** | 0.0192* | 0.0429*** | 0.012 | 0.0378*** | 0.0103 |
| | (0.0074) | (0.0075) | (0.0078) | (0.0076) | (0.0072) | (0.0075) |
| Age | −0.0003 | 0.0033*** | 0.0004 | 0.0036*** | 0.0005 | 0.0020*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Working hours/week | 0.0004 | 0.0003 | 0.0017*** | 0.0005 | 0.0008 | 0.0012** |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0005) |
| Constant | 0.3001*** | 0.1432*** | 0.2155*** | 0.1280*** | 0.3116*** | 0.1808*** |
| | (0.0323) | (0.0329) | (0.0345) | (0.0353) | (0.0418) | (0.0427) |
| N | 16,322 | 16,331 | 16,528 | 16,534 | 16,824 | 16,824 |
| adj. $R^2$ | 0.0801 | 0.1697 | 0.0668 | 0.1496 | 0.0838 | 0.1410 |

Note: * p<0.05, ** p<0.01, ***p<0.001; robust standard errors in parentheses. Source: BIBB/BAuA Employment Survey 2006, 2012, 2018; unweighted results.


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