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Grasping Digitalization in the Working World

An Example From the German National Educational Panel Study[1]

Abstract: Digitalization and automation have increased substantially in recent years and are reshaping the working world. These fundamental changes alter employee training needs and training programs. They create new employment opportunities, may cause excessive demands or raise fears of job loss. The extent of the societal transitions induced by the ongoing digitalization call for high-quality research data. In this paper, we introduce a new multi-dimensional survey module on digitalization and its consequences for the working world, which has recently been implemented in the adult cohorts of the German National Educational Panel Study (NEPS). We show how well and for which employee groups the newly developed survey questions capture experiences with digital technologies at the workplace. We test for the applicability of the instrument with regard to gender, age, education, and job tasks and show that it predicts employee's actual participation in further training. Moreover, we show the potential that results from the combination of the new survey module with further key strengths of the NEPS data such as its life-course or competence measures.

Keywords: Digitalization; Job Tasks; Further Education and Training; Survey Questions; NEPS

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1 The codes used in the present study are available for replications (https://doi.org/10.7802/2362).

 DOI: 10.5771/0038-6073-2021-4-415

https://doi.org/10.5771/0038-6073-2021-4-415 - am 29.01.2026, 17:11:12. https://www.inlibra.com/de/agb - Open Access -

Die Erfassung von Digitalisierung in der Arbeitswelt

Ein Beispiel aus dem Nationalen Bildungspanel

Zusammenfassung: Digitalisierung, der Einsatz vernetzter digitaler Technologien und Automatisierung haben in den letzten Jahren stark zugenommen. Sie prägen die heutige Arbeitswelt. Dieser tiefgreifende Wandel führt zu veränderten Weiterbildungsbedürfnissen und schafft neue Beschäftigungsmöglichkeiten. Aber er führt auch zu Überforderung oder der Angst vor Arbeitsplatzverlust. Das Ausmaß der durch die fortschreitende Digitalisierung induzierten gesellschaftlichen Veränderungen erfordert qualitativ hochwertige Forschungsdaten. In diesem Beitrag stellen wir ein neues mehrdimensionales Messinstrument zur Digitalisierung der Arbeitswelt vor, das in den Erwachsenenkohorten des Nationalen Bildungspanels (NEPS) implementiert wurde. Wir zeigen, wie gut und für welche Beschäftigtengruppen die neu entwickelten Items die Alltagsrealität am Arbeitsplatz abbilden. Wir prüfen die Anwendbarkeit des Instruments im Hinblick auf Geschlecht, Alter, Ausbildung und Aufgaben im Beruf und zeigen, dass es die tatsächliche Weiterbildungsbeteiligung von Beschäftigten vorhersagt. Darüber hinaus zeigen wir das Potenzial auf, das sich aus der Kombination der neu implementierten Items mit weiteren zentralen Stärken der NEPS-Daten – wie der Lebensverlaufserfassung und Kompetenzmessung – ergibt.

Stichworte: Digitalisierung; Job Tasks; Weiterbildung; Instrumentenentwicklung; NEPS

1 Introduction

Alongside many societies worldwide, Germany is experiencing an accelerating and far-reaching technological change in form of increasing digitalization and automation. The so-called fourth industrial revolution is not only enhancing highly automated and networked production processes and modifying our communication and information channels; it is also transforming our educational system and the world of work (BMBF 2017). In many areas, we can clearly observe the rise of digitalization, automation, and mobile robotics, for example, in production plants that were converted into "smart factories" with fully digitally networked manufacturing processes (Acemoglu/Restrepo 2019; Arntz et al. 2016; Arntz et al. 2017). For the society as a whole, however, the consequences of this transformation are rather difficult to assess. Effects on labor demand, occupations, worker's wages, qualification, and training needs are hard to predict and have triggered a debate about both the transformation's economic and individual opportunities and risks (Arntz et al. 2017, 2020 b; Chiacchio et al. 2018; Damioli et al. 2021 a; Damioli et al. 2021 b; Dengler/Matthes 2018; Genz et al. 2019; Kristal 2020).

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However, grasping the amount, the perpetuation and the consequences of digitalization in the working world is a complex task. Qualitative studies shed light on specific sectors, innovations, and companies (e.g., Briken et al. 2017; Pfeiffer 2019). Monothematic quantitative studies provide data on the dynamic of digitalization and selected implications for individuals and companies (Arntz et al. 2020 a; Nedelkoska/Quintini 2018; Pouliakas 2018). Ideally, aspects of digitalization should be addressed in data sources that focus on qualifications, skills, and returns to education in a longitudinal perspective. The setup of the German National Educational Panel Study (NEPS) already offers a wealth of data on qualification and labor market aspects. With the newly developed survey questions on digitalization in the working world, the NEPS data now have the potential to become a prime source for quantitative research on the opportunities and risks arising from digitalization and automation, on the likely winners and losers of these technological changes, and on how that transformation will affect lifelong learning, further education and training but also other dimensions such as health, family, and subjective well-being.

In this paper, we introduce the new survey questions on digitalization in the working world. Monitoring the structural and societal transformation and its consequences is essential for the social sciences to be able to produce high-quality research data and to provide evidence-based policy advice on fundamental social issues. Yet, it is hard to measure the technological change meaningfully in a population survey as the term digitalization is used and understood very differently across individuals, occupations, and industries. For example, in machine construction, ongoing digitalization fosters increasingly digitally networked and autonomous control of entire production processes. In service sector occupations, such as the judiciary, by contrast, digitalization occurs as artificial intelligence, automated text analysis and decision-making algorithms (Wirtz et al. 2018). In both areas, computers are substituting some tasks while supplementing others, which leads to very different consequences for the employees[2] working in the respective occupation (Damioli et al. 2021 b).

These examples highlight two central challenges when developing survey questions to record the digitalization of the working world for a representative population survey: The first challenge lies in the heterogeneity of the digitalization in the working world. It is necessary to provide a definition of digitalization that is both, broad enough to capture multiple pathways of digitalization, and precisely enough to distinguish digitalization from other technological transformations, such as automation. At the same time, for a population survey, the operationalization of digitalization must be comprehensible to employees across different occupations, industries, and qualification levels. Second, the digitalization in the working world continues to develop steadily, albeit at different speeds. To use the survey questions in a

2 Throughout this paper, we use the terms ‘employee’ or ‘worker’ to refer to all active persons in the labor market, regardless of whether they are self-employed or employed.

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panel questionnaire, they should be valid independent of time, but they must also be flexible enough to reflect the different speeds of development. Only if the survey questions address these features, they are suitable to capture the ongoing digitalization across occupations, industries, and qualification levels – and to provide a sound basis for analyzing its manifold social consequences.

In this paper, we show how well and for which employee groups the newly developed survey module adequately reveals workers' everyday reality in more or less digitalized and automated working environments. These survey questions were applied for the first time in the 2019/2020 waves of two adult surveys of the NEPS. We introduce this survey module and assess to what extent it is able to address the first challenge of capturing heterogeneity in the ongoing digitalization in the working world. Therefore, we test if the questions reliably reflect the answers of respondents of different gender, age, qualification levels, and job task types. Whether these survey questions also meet the second challenge will only become evident over time as new technological developments induce the need to revise or supplement specific items. In conclusion, we highlight the research opportunities made available with these new survey questions.

2 Theoretical Background

Digitalization and automation are expected to perpetuate the world of work. These processes are fundamentally transforming contents of jobs, skill requirements, and the systems of labor markets as a whole (Acemoglu/Restrepo 2019; Autor 2015; Bessen 2016; Brynjolfsson et al. 2017; Gregory et al. 2016; Pouliakas 2018). Computers continue to take over routine-based tasks, but they are also increasingly able to substitute non-routine, complex job tasks or to create completely new jobs (Damioli et al. 2021 b). As the contents of jobs are changing, and the skill requirements for the new world of work pose new demands and challenges on employees and employers, ICT skills, problem-solving skills and creativity are expected to become ever more important (Brynjolfsson/McAfee 2014; Mayer 2020). Educational systems and companies need to provide training and qualification programs to train individuals for tomorrow's labor markets and its life-long learning requirements (Fregin et al. 2020).

The degree to which digitalization and automation perpetuate the world of work, the degree to which they substitute routine and non-routine jobs, and the degree of cross-national variation in this transformation are open-ended issues. In contrast to predictions made by Frey and Osborne (2017), computers do not substitute entire occupations neither in the U.S., nor in Europe or Germany (Arntz et al. 2017; Dauth et al. 2018; Dengler/Matthes 2018; Graetz/Michaels 2018; Nedelkoska/Quintini 2018; Pouliakas 2018). On the contrary, while computers may replace certain tasks in some occupations, they supplement other tasks in other occupations (examples for Germany: Bonin et al. 2015; Dengler/Matthes 2015). In the inter-

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play between machines and humans, routine tasks are those most likely substituted by machines, while humans have a competitive advantage in problem-solving, adaptability, and creativity and can leverage this advantage in non-routine tasks (Autor 2015; Dengler/Matthes 2018). Thereby, a shift in the importance of social and cognitive skills that goes along with the digitalization of certain non-routine tasks becomes evident and can be observed in the high returns to such skills (Deming 2017).

Commonly the task-based approach of Autor et al. (2003) serves as the theoretical framing for explaining the employment and wage development effects of digitalization and automation. In recent decades, medium-skilled workers performing rather routine tasks experienced a lower development of employment and wages compared to high- and low-skilled workers, since routine tasks have the highest potential for substitution. While employment and wage polarization has been observed in many industrialized countries (e.g., Goos et al. 2014), evidence has only been found for polarization of employment (Spitz-Oener 2006), but not for wages in Germany (Antonczyk et al. 2009).

In line with the various manifestations of digitalization and automation in the working world, different theoretical concepts and definitions have been developed. Most of them conceive digitalization in the larger context of technological change that captures the fast and broad adaptation of new information and communication technologies. These changes, in turn, have the potential to fundamentally alter economic and work processes (BMAS 2020; Damioli et al. 2021 b), as they affect both, the organization of work in many industries and the qualification requirements of many workers. Focusing on the consequences of the ongoing digitalization on worker's skill requirements, working conditions, and working modes is particularly widespread in debates on the digital divide (Korupp/Szydlik 2005), including "future forms of cooperation between humans and machines, working hours, work organization, occupational health, safety and social security" (BIBB 2017: 11).

2.1 Definition

Various sub-fields of sociology, related disciplines, and stakeholders have difficulties agreeing on a definition of digitalization or digital transformation. Some focus on the technically-induced changes in specific applications, while others elaborate a more holistic approach viewing digitalization as a societal transformation that affects almost all areas of human life. Thus, in order to serve the manifold purposes of researchers who use population surveys like the National Educational Panel Study, we decided to develop a concept of digitalization that captures both, a narrow understanding of digitalization focusing on networked digital innovations, and a broad understanding including (societal) consequences of the use of networked digital innovations.

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Digitalization shall be defined as a socio-technical process that is characterized by three elements: first, the introduction of networked digital technologies; second, the introduction of application systems that build upon these networked digital technologies; and third, the connection of these systems to a networked infrastructure that runs more or less autonomously based on the data generated by the application systems (cf. Hirsch-Kreinsen 2015). The technical part of this socio-technical process is represented by the introduction and the increasing use of networked digital technologies. The social part covers structural transformations with respect to skill requirements, job tasks, tenure, quality of work, and social inclusion into the working world. In contrast, we understand *automation* as the increased use of self-controlling, largely autonomously deciding and acting computer-controlled machines (Friedrich et al. 2022).

With these definitions of digitalization and automation, we seek to relate to a broad range of the working population in different occupations, industries, and qualification levels to meet the challenge of capturing the heterogeneity in digitalization. Such a broad definition allows us to focus on the large variety of consequences for different subgroups of the workforce. For example, in occupations where increasing automation mainly replaces manual routine tasks, blue-collar workers are more strongly affected than others (Acemoglu/Restrepo 2020; Dauth et al. 2018). In contrast, the increasing use of networked digital information and communication technologies substitutes manual and cognitive routine tasks but supplements complex analytical and interactive non-routine tasks, thereby mostly affecting white-collar workers (Autor et al. 2003).

The speed of these changes is largely driven by companies' investment decisions (Arntz et al. 2016; Damioli et al. 2021 b). As the target unit of population surveys (like NEPS) are individuals, we cannot quantify the speed of digitalization or automation of workplaces or their consequences on companies' performance and employment strategies. Thus, by design of the NEPS study, the supply side remains inaccessible. Instead, we focus on the employees' subjective perception of changes in the digitalization of workplaces, as well as resulting consequences for individual qualification needs and future employment prospects such as perceived risks of losing a current job or perceived chances of finding a new one. As some scientific and public debates focus on potential negative labor market consequences of digitalization fueling job and employment insecurities of employees (Hipp 2019), measuring future labor market prospects was an important part of the newly developed survey module for providing evidence-based policy advice.

2.2 Hypotheses

Although the digitalization in the working world gains momentum across industries and occupations, differences in its forms, consequences, and pace remain. Drawing on the literature and theoretical considerations, we provide corresponding hypothe-

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ses on inter-group differences indicating how the digitalization in the working world and its consequences should vary with regard to i) gender, ii) age, iii) qualification levels, and iv) job task types. If the newly developed survey module on digitalization validly reflects the perpetuation and consequences of digitalization, the survey questions should reveal these inter-group differences in perceptions and expected consequences for qualification needs, feelings of excessive demands and job risks.

First, regarding gender-related differences, women benefitted more than men from the first wave of computerization as of the 1980ies, as physical strength became less important (Black/Spitz-Oener 2010; Weinberg 2000). Furthermore, additional technological changes started to replace routine tasks and thus mostly affected traditionally male-dominated jobs (Autor et al. 2003; Brynin 2006; Goos et al. 2014). However, fewer women chose ICT-related fields of study (Hill et al. 2010) while men tended to prefer programming-intensive jobs (Cheng et al. 2019; England et al. 2020). Considering that women are more often employed in the less automated and digitalized service sector, combined with gendered labor market segments (Achatz 2018), we assume that *women show lower levels of digitalization of their workplaces than men, resulting in fewer qualification needs and fewer perceived consequences* (*hypothesis 1 on gender differences*).

Second, age is seen as a challenge to worker's ability to engage with new technologies, although the concept of 'digital natives' is discussed quite controversially in the literature (Helsper/Eynon 2010). In general, aging implies certain losses in cognitive abilities (Czaja et al. 2001) and older generations may have been used to a slower working pace with less need for intense learning and continuous updating (Mauno et al. 2019). In addition to the age and cohort argument of decreasing adaptability, older individuals use new technologies less frequently in the private sphere, thereby losing opportunities to train digital capabilities (Neves/Mead 2020). We therefore assume that due to both employer-based selection and employee-based self-selection processes, *older workers report lower levels of digitalization of their workplaces than younger ones, which is also reflected in lower qualification needs and perceived consequences* (*hypothesis 2 on age differences*).

Third, the use of digitally-networked and further new technologies is differently distributed across qualification levels: lower qualified individuals, compared to highly qualified ones, use computers and the internet less frequently and for different purposes (Korupp et al. 2006). The daily workload resulting from networked digital technologies also increases more with rising qualification levels. Thus, higher qualified workers experience increasing cognitive and social demands combined with a large amount of information to be processed, both of which reach levels which may become difficult to handle (Arnold et al. 2017). In contrast, low qualified workers report physical relief provided by new technologies in routine tasks and face higher levels of automation at their workplaces. In our *hypothesis 3 a* we accor-

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dingly assume that *higher qualified workers face higher levels of networked digital technologies at their workplaces than employees with lower formal qualification*. Thus, we expect that higher qualified workers have stronger qualification needs. At the same time, *for lower qualified workers, we expect to find higher workplace automation than for those with higher qualifications* (*hypothesis 3 b on differences with regard to qualification levels*).

Fourth, we expect that new technologies substitute manual and cognitive routine tasks while they may supplement complex analytical and interactive non-routine tasks (Autor 2013, 2015). Accordingly, depending on the main task type, some occupations are subject to more pervasive consequences of workplace digitalization concerning the organization of work or training needs than others (Dengler/Matthes 2018). For occupations where analytic and interactive tasks as well as an autonomic way of working dominates, we assume to find a higher level of workplace digitalization, more qualification needs, and positive assessments of future labor market chances (*hypothesis 4 on inter-group differences w.r.t. job tasks*). In contrast, when an occupation's manual and routine tasks prevail, we assume a subjectively perceived higher risk of job loss (*hypothesis 5 on inter-group differences w.r.t. manual/routine tasks*) and a lower level of reported workplace digitalization, fewer qualification needs, and a negative assessment of future labor market chances (*hypothesis 6 on inter-group differences w.r.t. task types*).

3 Data and Methods

3.1 Data

The German National Educational Panel Study (NEPS)[3] is an excellent data source to study competence development, educational participation and returns to education over the life course (Allmendinger et al. 2019; Blossfeld et al. 2011). We use data from the Adult Starting Cohort (SC6) of the NEPS (SC6:12.0.0; doi:10.5157/NEPS:SC6:12.0.0), wave 12 from the years 2019/2020. We combine the data of the scientific use file (SUF) with consortium data that provide additional information needed for our validation analyses. The NEPS-SC6 is a representative sample of the population in Germany in 2009 and covers respondents born between 1944 and 1986. Given our focus on digitalization in the working world, we restrict our analysis sample to employed persons only. A total of N = 4,694 individuals reported valid answers for the digitalization items and provided information on gender, age, education, and job tasks. The respondents of this analysis sample are on average

3 From 2008 to 2013, the NEPS data was collected as part of the Framework Program for the Promotion of Empirical Educational Research funded by the German Federal Ministry of Education and Research (BMBF). As of 2014, NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi) at the University of Bamberg in cooperation with a nationwide consortium.

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52.5 years old, 47.7% are female and 15.6% have a migration background.[4] Furthermore, 4.7% have no school leaving certificate or vocational training qualification, 11.9% have a lower secondary school leaving certificate ("Hauptschulabschluss") with vocational training, 29.6% have an intermediate secondary school leaving certificate ("Mittlere Reife") with vocational training and 19.2% have a higher secondary school leaving certificate ("Abitur") with vocational training, while 34.6% have a university degree.

3.2 Measurements on Digitalization and its Consequences

We developed a new questionnaire module to assess the permeability of digital technologies and its consequences in the working world of adults.[5] According to our broad definition of digitalization, networked digital technologies refer to, for example, the use of online forums, e-mails, tablets, clouds, and self-controlled or self-learning computer systems. Complementarily, we ask about the permeability of the workplace's automation. The respondents are invited to assess how strongly their workplace is shaped by networked digital technologies and automation, what kind of networked digital technologies they use at work, and how they subjectively assess the consequences of the spread of networked digital technologies for their personal job prospects. In more detail, the survey questions distinguish five dimensions of digitalization and its consequences (see Table 1).[6] First, three questions refer to the perpetuation of digitalization and automation in the respondent's particular job and work place and how the respondent's job changed due to networked digital technologies. Second, two questions capture needs for further training and qualification arising due to networked digital technologies. Third, an affective component regarding a respondent's heteronomy and information overload is assessed by two questions. Fourth, a battery of items captures the extent of digitalization at a job by inquiring about the use of certain technologies with an increasing difficulty level ranging from using the internet to search for information to programming algorithms. Fifth, we ask about the respondent's labor market prospects concerning the risks of losing the current job and the general future employability resulting from digitalization.

4 The respondent was not born in Germany or has at least one parent who was not born in Germany.

5 The questionnaire module was fielded in the sample of adults (NEPS SC6) as well as in a sample of former adolescents (NEPS SC4). However, in the present paper we analyze only the SC6, as the share of fully employed individuals in SC4 is still relatively small and the sample is restrictive with regard to educational qualifications. Nevertheless, SC4 also will be a promising database for analyzing digitalization in the world of work in the future.

6 See Table A1 in Appendix for SUF variable names, the wording of the questionnaire module and its rationale. Refer to Friedrich et al. (2022) for more details on the intentions of implementing each item and how the item maps to our theoretical considerations.

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Table 1: Dimension and content

Dimension	Item
D1: Perpetuation of networked digital technologies and automation	■ Job characterized by networked digital technologies (NDT) (**D1 a**) ■ Changes in usage of NDT at the workplace over time ■ Job characterized by automation (**D1 b**)
D2: Qualification needs	■ Constant development of skills needed due to NDT ■ Preparedness for NDT
D3: Affective impact of digitalization	■ Feeling controlled by NDT ■ Information overload by NDT
D4: Use of networked digital technologies	For each technology, first the use (yes/no) and if yes frequency of use is surveyed: ■ Searching for information via the internet/intranet ■ Creating or editing digital files ■ Exchanging digital files ■ Maintaining websites ■ Creating websites ■ Programming algorithms for intelligent systems
D5: Labor market prospects	■ Risk of losing current job due to NDT ■ Chances of finding new job changed by NDT

The survey questions underwent a complex and rigorous development process to ensure functionality in our target population of working adults. First, we developed the concept for the specific questions based on literature research, on comparisons with monothematic digitalization surveys, and with the help of experts on digitalization. Second, we went through two rounds of cognitive pretesting with stepwise improvements to make sure the questions work as expected across various groups. All cognitive pretests included additional probing questions addressing the respondent's understanding of our questions and asking how they arrived at their answers. We thereby assured our questions' comprehensibility and eliminated problems arising due to a different understanding of digitalization across respondents. As it was particularly important to achieve a similar understanding of the term digitalization without offering respondents a specific definition that would have limited their personal perspective, we started with heterogeneous examples for networked digital technologies and narrowed them down through cognitive pretesting. For the use of networked digital technologies, we strongly relied on the European reference framework for the assessment of digital competencies (Carretero et al. 2017) and tested these items in cognitive pretests as well. Finally, we fielded a quantitative pretest

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conducted by the *Zentrum für empirische Sozialforschung* at Humboldt University Berlin interviewing 222 respondents based on a random sample quoted by education in computer-assisted telephone interviews. Further information on the development process, the samples of pretesting groups and results are provided in Friedrich et al. (2022).

3.3 Main Variables

The key variables for our analyses are the newly developed items on digitalization. For the analyses, we recoded the items so that high values indicate high agreement with the statements. In addition, the NEPS data offer the unique opportunity to link our measures of digitalization to measures of job tasks. The five job task types (analytic, interactive, manual, routine, and autonomy) were assessed in the 2019/2020-wave of NEPS-SC6 by a questionnaire developed and described by Matthes et al. (2014). The analytic task type consists of the three subscales reading (4 dichotomous items), writing (4 dichotomous items), and mathematics (7 dichotomous items). The three subscales are combined into a total scale, which is standardized to a 0–1 range. The items of the remaining task types were each answered on a 5-point answering scale (1 = always/very often, 2 = often, 3 = sometimes, 4 = seldom, 5 = very seldom/never) and combined into one scale each for the interactive (6 items), manual (5 items), routine (6 items), and autonomy (4 items) task types. These scales are also recoded and standardized to a range from 0–1, with 0 indicating low values and 1 indicating high values on the task types.[7]

For the analyses of the aspects of digitalization and its correlations with socio-demographic characteristics, we include gender, age, and five educational groups: (1) respondents without any vocational training, (2) respondents with lower secondary education ("Hauptschulabschluss") plus vocational training, (3) respondents with intermediate secondary education ("Mittlere Reife") plus vocational training, (4) respondents with higher secondary education ("Abitur") plus vocational training, and (5) respondents with any kind of university degree. Further, we use information on whether participants provided an e-mail address for contacting them and information from an ICT competence measure. The ICT-test is based on a framework that includes several process components (access, create, manage, evaluate) and software applications (word processing, spreadsheet/presentation software, e-mail/ communication software and internet/search engines) that individuals need for handling information and communication technologies in a modern world. For further details, see Senkbeil and Ihme (2015). Lastly, we use information on whe-

7 In our analyses, we refer to job task types and not to occupational groups. We chose this approach for two reasons: first, in exploring the fit of our digitalization items for different subgroups, we follow the task-based approach, which focuses on job tasks rather than occupations. Second, different tasks can also be used within an occupation, so that occupational groups have a high task diversity (Dengler et al. 2016). Therefore, we do not control for occupational groups at the same time so as to not over-specify our models.

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ther respondents participated in non-formal adult education since the last interview (i.e., about 12 months ago).

3.4 Statistical Analyses

To test our hypotheses, we conduct several descriptive analyses as well as multiple regression analyses. Gender, age, education, and job task types are the key independent variables in most analyses.

First, to gain a better impression of how well different groups of participants understood the items, we analyze the time participants needed to answer the items. The time is automatically measured after every dimension with a timestamp. In order to investigate whether certain groups processed the dimensions particularly quickly or slowly – and thus infer information about the respondent's process of understanding of the questions – we calculate t-tests and analyses of variance with gender, age, education, and job task types. For the task types, we split the sample at the median of each job task type and then compare the two resulting groups. For the timestamps, we only investigate dimensions 1, 2, 3, and 5 because in dimension 4 (use of networked digital technologies), participants had to answer different numbers of items and therefore timestamps are not comparable.[8]

Second, we calculate Pearson's correlations between the digitalization items and gender, age, education (Spearman's correlation), and job task types. In addition, to assess the validity of our survey questions, we calculate correlations between the digitalization items and an ICT competence test and the information whether participants in the NEPS-SC6 study provided an e-mail address. We regard this additional information for several reasons: We expect that respondents with high ICT skills are also likely to be more affected by digitalization and the use of networked digital technologies. Furthermore, we assume that these respondents also state that they are more strongly influenced by digitalization and use digital technologies to a greater extent. Additionally, participants who are more affected by digitalization should also more likely have an e-mail address and should be – on average – more willing to provide it for the NEPS study. Respondents who are more affected by digitalization may also prefer to communicate by e-mail and are therefore also more likely to provide their e-mail address.

Third, we investigate whether group differences exist using multiple OLS regressions on each digitalization item as dependent variable. For dimension four, we refrained from running a model on each item separately and instead used an aggregated index. We created this index by summing up all items asking for the use of specific digital technologies. This aggregation is substantiated by the conceptualization of these items as a scale measuring the level of digitalization of the respondent's

8 If respondents did not use any of the first three networked digital technologies, they were filtered to the next dimension in the questionnaire.

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occupation according to Carretero et al. (2017). Accordingly, the higher a respondent's value on the index, the more complex is the respondent's use of networked digital technologies. In each of the OLS models, we investigate the effect of age,[9] gender, and education on the respondents' assessment of each item. Then, we explore whether job tasks influence the assessment of the digitalization items. Therefore, we also estimate multiple linear regression models on each digitalization item as dependent variable but include all job task types as explanatory variable while controlling for age, education, and gender.

Fourth, we investigate the relationship between further training participation since the last interview and digitalization. For these analyses, we estimate linear regression models using the number of further training courses reported since the last interview as the dependent variable. We run several models with each digitalization item as the key explanatory variable while controlling for age, age^2, education, and gender. All results are displayed as coefficient plots.[10]

4 Results

First, we calculated descriptive statistics (min, max, mean, standard deviation, skewness, number of observations, share of missings) for both the analysis sample and the total sample to check how the items are distributed in the samples, respectively. These statistics are reported in Table A2 and A3 in the Appendix and they display no noticeable result.

Second, we analyzed timestamps to investigate whether certain groups processed the questionnaire particularly quickly or slowly (Table A4 in the Appendix). Especially in dimension 5 (future prospects), there are significant differences with respect to gender, age, education, and type of job task. Although the differences in response time are statistically significant, they are very small – thus, these differences hardly seem substantially important. In the other dimensions, significant differences are only occasionally observed. Taken together with the small differences in dimension 5, the timestamp analysis suggests an overall satisfying understanding of the survey questions, and no indication of substantial differences across groups.

Third, we calculate correlations between all digitalization items and gender, age, education, the five job task types, ICT competence, and the information whether respondents provided their e-mail address as shown in Table 2.

9 We also estimated models including higher polynomials of age. Though we found significant effects for age^2, the effect size did not substantially alter the linear relationship. Therefore, age^2 was dropped from all models using the digitalization items as dependent variables.

10 The respective regression tables are included in the Appendix.

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Table 2: Correlations

	Female	Age	Education	Analytic	Interactive	Manual	Routine	Autonomy	ICT	E-mail
Networked (D1 a)	-.10 ***	-.13 ***	.21 ***	.37 ***	.13 ***	-.30 ***	-.38 ***	.17 ***	.28 ***	.16 ***
Automation (D1 b)	-.04 **	-.05 ***	-.05 ***	.03 *	-.04 **	-.09 ***	-.09 ***	-.03 *	-.07 ***	.02
Activity change (D1 a)	-.01	-.08 ***	.11 ***	.22 ***	.22 ***	-.10 ***	-.26 ***	.09 ***	.08 ***	.11 ***
Further training needs (D2)	-.08 ***	-.08 ***	.18 ***	.39 ***	.23 ***	-.20 ***	-.44 ***	.20 ***	.21 ***	.15 ***
Prepared (D2)	-.14 ***	-.13 ***	.18 ***	.34 ***	.12 ***	-.27 ***	-.31 ***	.22 ***	.31 ***	.17 ***
Feeling controlled (D3)	.02	.05 ***	-.03 *	.06 ***	.11 ***	.01	-.13 ***	-.05 **	-.12 ***	-.02
Information quantity (D3)	-.05 ***	.00	.12 ***	.27 ***	.16 ***	-.13 ***	-.28 ***	.11 ***	.05 **	.08 ***
Index use (D4)	-.12 ***	-.17 ***	.42 ***	.58 ***	.26 ***	-.38 ***	-.43 ***	.35 ***	.49 ***	.27 ***
Job loss (D5)	.01	-.02	.01	-.01	-.02	-.09 ***	.00	-.05 ***	.04 *	.00
Labor market chances (D5)	-.10 ***	-.24 ***	.14 ***	.22 ***	.12 ***	-.07 ***	-.24 ***	.16 ***	.24 ***	.11 ***

Note: For education, Spearman's rank correlation coefficient was calculated instead of Pearson's correlation.
Source: Authors' own calculations based on the NEPS-SC6 wave 12.

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Overall, the digitalization items mostly correlate negatively with gender (female = 1) and age as well as positively with education, the test score in ICT competence, and the information whether participants provided an e-mail address. This is in line with our *gender hypothesis* (H1: women show lower levels of digitalization of their workplaces than men), *age hypothesis* (H2: older workers report lower levels of digitalization of their workplaces than younger ones) and our *higher qualification hypothesis* (H3 a: higher qualified workers face higher levels of networked digital technologies at their workplaces than workers with lower formal qualification). Further, the digitalization items mostly correlate positively with analytic, interactive, and autonomy tasks and negatively with manual and routine tasks. This is in line with our *task hypothesis* (H4: for workers dominantly performing analytic and interactive tasks as well as an autonomic way of working, we assumed a higher level of workplace digitalization) and our *manual-routine hypothesis* (H6: when manual and routine tasks prevail in a job, we assumed a lower level of workplace digitalization). Of particular interest are the correlations with the sum index in dimension 4 (Index use (D4)) that reflects the number of networked digital technologies used at the workplace. In dimension 4, participants are first asked whether they use several networked digital technologies and if they use a particular technology, they are asked how often they use this technology. Thus, on the one hand, the correlation results show which individuals tend to use a high number of networked digital technologies. On the other hand, the results show indirectly which individuals answered the frequency of use questions in particular. Male, younger, and more educated respondents as well as respondents working in jobs with high levels of analytic, interactive, and autonomy tasks and a low level of manual and routine tasks stated that they use more networked digital technologies. And as a consequence, these individuals also answered the questions on frequency of use. Thus, the frequency of use items in dimension 4 only include a reduced number of participants.

We now turn to discussing our results of the regression models with each digitalization item as a dependent variable in more detail. We observe statistically significant associations for gender, age, and education when including these explanatory variables together in each of the models. Figure 1 depicts the first set of models including gender, age, and education. Most of the empirical findings of these models are in line with our expectations, specifically with our *gender (H1), age (H2)* and *higher qualification hypotheses (H3 a)* and partially with our *lower qualification hypothesis* (*H3 b:* we expected to find higher workplace automation for lower qualified workers than for those with higher qualifications). However, we also find differences across the digitalization items in terms of the associations with gender, age, and education. For example, we find no significant association between the independent variables and respondents' assessments of their risk of job loss (M9), whereas every explanatory variable is statistically significantly associated with networked digital technologies (M1).

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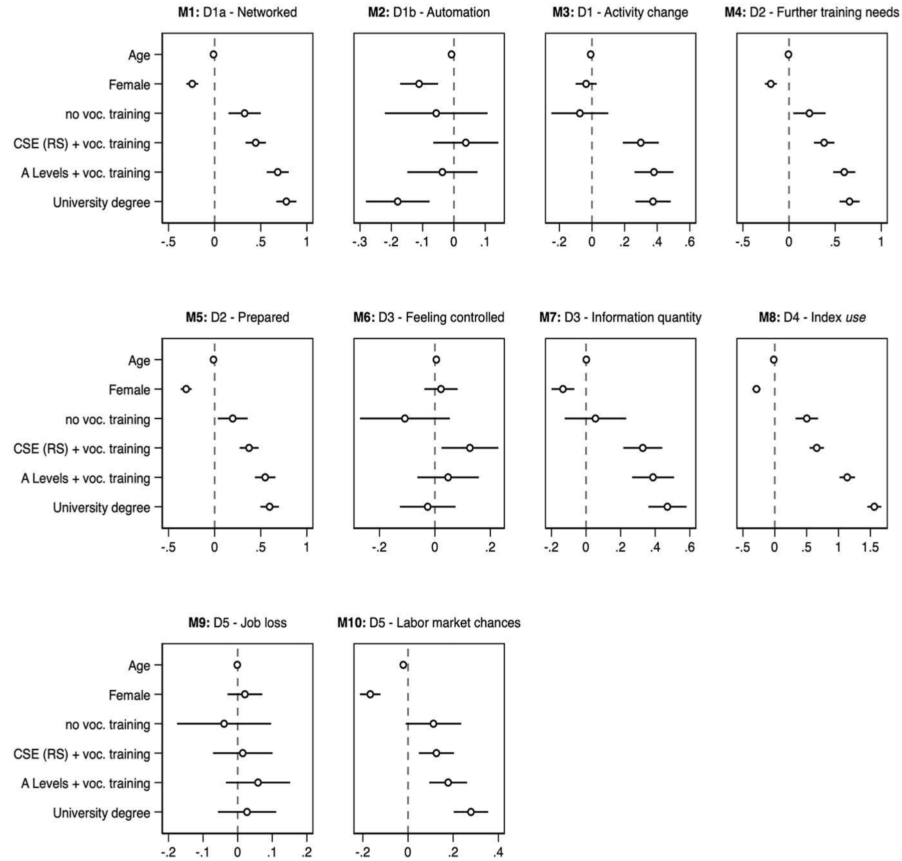
Figure 1: Coefficient plots of multiple OLS models using each digitalization item as dependent variable



Note: Each plot represents one model using a different digitalization item as the dependent variable. In each case, higher values of the dependent variable indicate higher agreement or frequency. The reference category for each education variable is lower secondary school leaving certificate with vocational training. Appendix Table A5 presents the full models.
Source: Authors' own calculations based on the NEPS-SC6 wave 12.

For most items we find that respondents' agreement or frequency is lower among women than among men (*gender hypothesis H1*) and higher among the higher qualified than among those having lower formal qualifications (*higher qualification hypothesis H3 a*). Our model predicting the fourth dimension of our digitalization module, the usage index (Figure 1, M8), can best verify the qualification assumption. Here, we observe that the higher education levels seem to be strongly associated with the use of more complex networked digital technologies. Our findings for automation suggest that a higher level of differentiation is needed. Although we

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assumed higher workplace automation at jobs with lower qualifications compared to jobs with higher qualifications (*lower qualification hypothesis H3 b*), we only find a statistically significant difference, that is in line with our hypothesis, between university degree versus lower secondary school leaving certificate with vocational training (Figure 1, M2). All other qualification levels, except the university degree, seem to be equally strongly associated with workplace automation. Moreover, although the effect of age seems rather small in all Figures, it should be noted that the effect for someone of average age in our sample is similar to the effect of having higher education as compared to the reference group (*age hypothesis H2*). For a closer look on the age effects see Appendix Table A5.[11]

To test *hypotheses 4* to *6* addressing the role of job tasks, we estimate further linear regression models including all job task types as key explanatory variables. We included gender, age, and education in all models as control variables.

The results shown in Figure 2 support our *task hypothesis (H4)* and our *manual-routine hypothesis (H5)*, while *the automation hypothesis* (H5: when manual and routine job tasks outweigh, we assume both a higher level of automation and a subjectively perceived higher risk of job loss) finds no support according to the regression models on automation (Figure 2, M2) and job loss (Figure 2, M9). We find that if analytic tasks are predominant, workers assess their workplace to be more strongly characterized by networked digital technologies and they report having more qualification needs. At the same time, those respondents are more prepared for working with digital technologies, use more complex networked digital technologies and have a positive assessment of their future labor market chances. We observe a similar relationship for interactive as well as autonomy task types. However, the effect size is considerably smaller than for analytic tasks and we do not find statistically significant associations. This means that although our *task hypothesis (H4)* holds true in general, the story differs between analytic, interactive, and autonomy tasks.

11 A further notable finding concerning age is that it mostly follows a linear trend. However, when including age^2 we find that the relationship between age and most digitalization items is almost zero or somewhat increases up to a certain age and then sharply declines. For dimension D3, we find the opposite relationship. These findings might substantiate the cohort argument.

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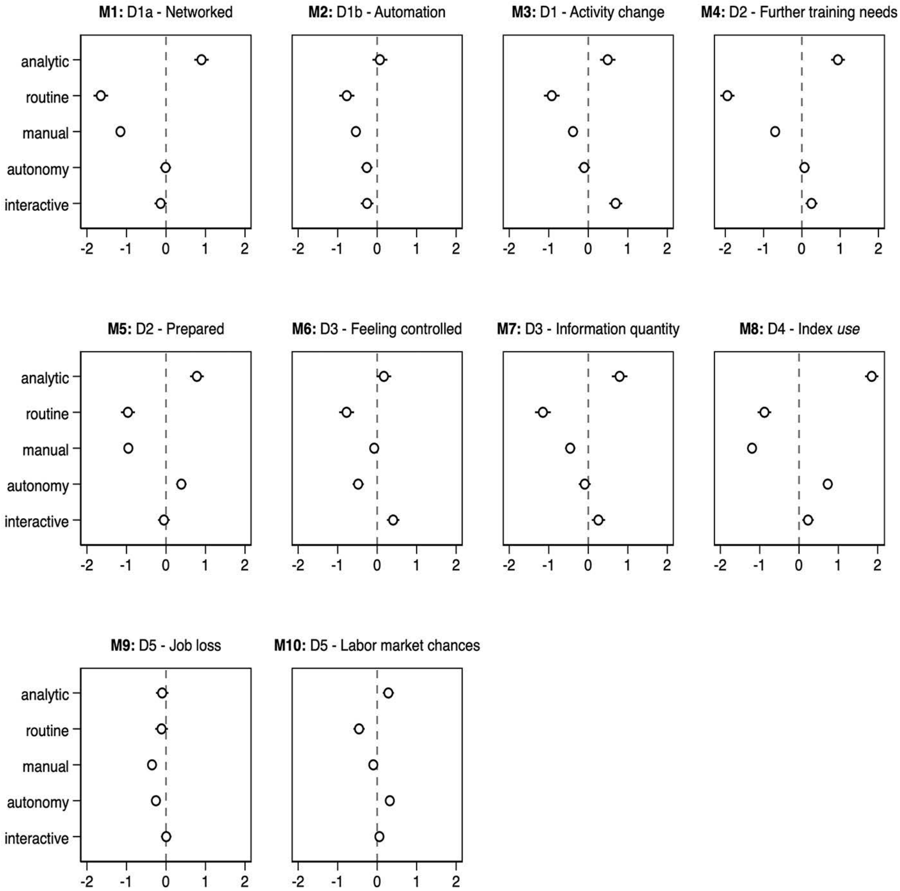
Figure 2: Coefficient plots of job task types (derived from OLS models)



Note: Each plot represents an extract from a model using a different digitalization item as the dependent variable. Higher values of the dependent variable indicate higher agreement or frequency. Age, gender, and education are included as control variables in each model. Appendix Table A6 presents the full models.
Source: Authors' own calculations based on the NEPS-SC6 wave 12.

In contrast, as assumed by *our manual-routine hypothesis (H6)*, performing mainly manual or routine tasks is statistically significantly associated with having a lower level of workplace digitalization, less qualification needs, and a negative assessment of future labor market chances. The findings also suggest that, although workers mainly performing routine or manual tasks have fewer qualification needs, they feel less prepared for actually working with networked digital technologies. We expected that manual and routine tasks are also associated with a higher level of automation (*automation hypothesis H5*). Instead, we find a negative association of manual tasks

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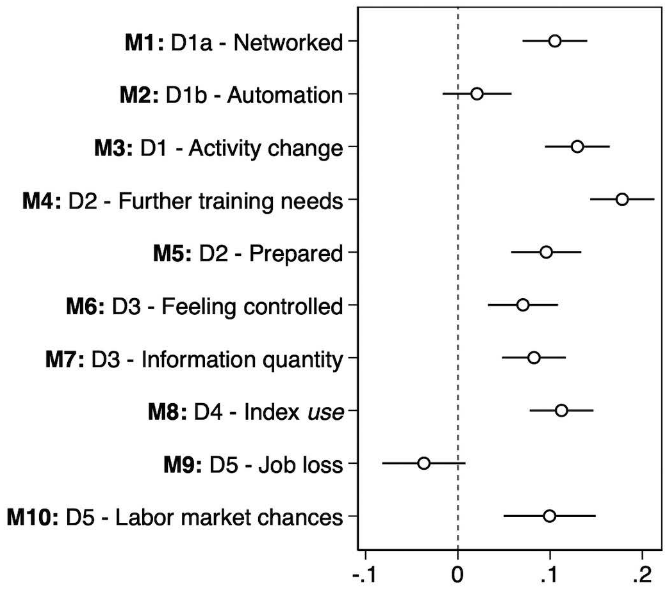
with the perceived risk of job loss and no statistically significant relationship for routine tasks.

On an interesting side note, when including job tasks as explanatory variables, we find that our sociodemographic variables remain largely statistically significant and substantively relevant (compare Appendix Table A6 and A7). For example, even when we account for different job tasks, gender still has the same statistically significant associations with most digitalization items. Overall, the effect sizes of sociodemographic variables remain meaningful despite including job tasks, which further substantiates *hypotheses 1* to *3 a* and improves our estimation for *hypothesis 3 b*. Nonetheless, job tasks are stronger in predicting response differences than the sociodemographic variables.

Figure 3: Coefficient plots of the number of further training courses (OLS models)



Note: Each line represents an extract from a model using a different digitalization item as the key explanatory variable. Higher values on the digitalization item indicate higher agreement or frequency. Appendix Table A7 shows the full models.
Source: Authors' own calculations based on the NEPS-SC6 wave 12.

Lastly, complementing and assessing the robustness of the empirical evaluations of our hypotheses regarding the relationship between digitalization and *perceived* qualification needs, we conduct further regression models exploring how our digitalization items are associated with *actual* participation in further training. We operationalize the latter by the number of further training courses respondents participated in the past twelve months before the interview, which is measured yearly in the

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NEPS-SC6 life course measurement. Of the various dimensions covered by our questionnaire module, we investigate the associations between the level of networked digital technologies at the workplace (D1 a), perceived workplace automation (D1 b), qualification needs (D2), feelings of loss of control and information overloads (D3), expected labor market prospects (D5), and the actual level of new technology usage (D4) on the one hand and actual further training participation on the other. In each case, we include all sociodemographic control variables and run separate models for each dimension as the key explanatory variable. Figure 3 presents the main results.

We find that almost all dimensions are associated with higher rates of further training participation since the last interview. Most of these relationships are rather intuitive. For example, the models predict that respondents who perceive more further training needs due to networked digital technologies report having attended at least one further training course. Similarly, reporting an information overload by increasing digitalization or feeling controlled by networked digital technologies is associated with a higher number of reported further training courses. The same pattern becomes apparent for the fourth dimension of our survey questions on digitalization, i.e. the actual use of networked digital technologies at the workplace. Finally, we want to highlight the relationship between preparedness and course attendance. Since our models show associations and not causal effects, we assume that respondents attended courses prior to being interviewed and that they feel more prepared due to this previous course attendance. We also find a notable difference in the relationships between networked digital technology and automation with further training participation respectively. While we find the expected positive association for respondents who report having jobs that are characterized by networked digital technologies, we do not find that association for those who report having a job characterized by automation.

5 Conclusion

Digital technologies permeate everyday life. In particular, the process of digitalization reshapes the world of work in industrialized societies like Germany. Several – mostly qualitative – studies offer narratives on how this process of digitalization is implemented and which implications it has for individuals, companies, and labor market sectors (Briken et al. 2017; Pfeiffer 2018, 2019). Likewise, a few quantitative monothematic studies try to assess the state of digitalization and potential ramifications of this process (Arntz et al. 2020 a; Nedelkoska/Quintini 2018; Pouliakas 2018). Being designed as a longitudinal population panel, the National Educational Panel Study is an excellent setup to monitor the process of digitalization in individuals' everyday life, especially with respect to changes in the working world. With its detailed measures on job tasks, with additional information on job characteristics and job satisfaction, its sophisticated measures on cognitive and non-cognitive com-

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petencies (including ICT skills), and with its fine-grained measures of educational degrees and participation in further training, the NEPS data offer a very rich set of dimensions and variables.

In this paper, we introduced newly developed, comprehensive survey questions on various aspects of digitalization at the workplace. Differentiating five dimensions – permeation of the workplace by networked digital technologies and automation, use of networked digital technologies, induced qualification needs, affective consequences, and labor market consequences – the new survey questions in the NEPS data offer ample opportunities to address research questions on the process of digitalization and its consequences for individuals. In addition to the demonstrated potentials in analysing the relationships between digitalization and participation in further training, the new items can also be used to investigate relationships between digitalization and job characteristics like opportunity for promotion, job security, appropriate wages, fit between qualifications and job requirements or work-family balance. Thus, the research opportunities on work and employment quality with the NEPS data is now supplemented by digitalization and automation. Combining questions on risk tolerance or on the importance of on-the-job learning can, for example, reveal how individuals assess the increased need for further training as a result of digitalization in order to cope with technological change. Other, non-economic factors of everyday life can also be linked to the digitalization and automation of work processes with the NEPS data, such as social and political attitudes, health, and satisfaction in general or with work. Most of these questions are collected as panel items. Thus, the newly developed questions offer ample potential for exploring various issues of social inequality and their development through technological change in workplaces.

In line with our hypotheses, our analyses have shown that men and women, older and younger respondents as well as more educated compared to less educated individuals are exposed differently to workplace digitalization. Women, older, and less educated respondents are generally less affected by the introduction of networked digital technologies, addressing questions of technologically induced or perpetuated social inequalities. However, these inequalities largely mirror existing labor market inequalities. Women, older, and less educated employees find themselves in jobs that are less favorable in terms of income, prestige, and job security, often also in terms of the actual tasks they perform on the job. We have shown that job tasks indeed correlate with different dimensions and degrees of digitalization and with the consequences for the increasing digitalization.

As we identified the heterogeneity of digitalization and its continuous development as two main challenges for the sound measurement of digitalization in the working world in representative panel surveys, the purpose of our analyses has been twofold: First, we have shown that the new measures on digitalization and its consequences capture key aspects of the process of digitalization. The correlations with sociodemographic characteristics and with specific job tasks largely follow the theoretical

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expectations and earlier findings. Hence, the new module can be considered to be a robust measure for the description and the analysis of the process of digitalization at the workplace applicable across various population subgroups. Second, our analyses provide insights into the enormous potential of the NEPS data, now becoming even bigger with a new and robust measure of digitalization and its consequences.

Yet, we want to point out three limitations and open questions of the new questionnaire module in the NEPS data. First, NEPS surveys individuals, thus we have little information on the permeation of digitalization in a given company. As companies are main drivers of technological change, additional company surveys are needed to complement the analysis potential we provide on the individual level. For the time being, we need to assume that digitalization is a process happening outside of the respondent, i.e. at the workplace and in a company, to which the respondent has to adapt. Second, we developed the items for the context of the working world and employed individuals. Therefore, we cannot provide analyses on the opportunities for the population of the unemployed or for the private sphere.

Third, we distinguish the two sub-dimensions of networked digital technologies and automation in the perpetuation dimension of our questionnaire module because each of them matters to a varying degree in different industries, occupations, and tasks. Yet, the overall picture is that our data is currently less-well suited for analyzing automation processes than it is for studying the spread of networked digital technologies at the workplace. Like in many long-running panels, there are meanwhile just too few ("blue-collar") respondents left working in branches or occupations that are subject to wide-spread automation, which is also reflected in large standard errors of the automation variable in our regression analyses. Similarly, while our respondents report few automated processes at their workplaces, they perceive their workplaces as strongly characterized by networked digital technologies. We also found only small associations between automation and age, qualification levels and task types and no association with actual participation in further training. For now, it remains an open question whether the differentiation of networked digital technologies and automation is worthwhile, especially with regard to studying its consequences on individual competence development, employment careers, job satisfaction, and further training needs, as intended. Despite these limitations, our new survey instrument provides ample opportunities for future research. We invite researchers to exploit this rich set of opportunities for their own analyses on digitalization, its origins, and consequences.

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References

Acemoglu, Daron & Restrepo, Pascual (2019): Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives* 33(2): 3–30. https://doi.org/10.1257/jep.33.2.3

Acemoglu, Daron & Restrepo, Pascual (2020): Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy* 128(6): 2188–2244. https://doi.org/10.1086/705716

Achatz, Juliane (2018): Berufliche Geschlechtersegregation, in: Martin Abraham & Thomas Hinz (Ed.), *Arbeitsmarktsoziologie.* Wiesbaden: Springer VS. pp. 389–435.

Allmendinger, Jutta, Kleinert, Corinna, Pollak, Reinhard, Vicari, Basha, Wölfel, Oliver, Althaber, Agnieszka, Antoni, Manfred, Christoph, Bernhard, Drasch, Katrin, Janik, Florian, Künster, Ralf, Laible, Marie-Christine, Leuze, Kathrin, Matthes, Britta, Ruland, Michael, Schulz, Benjamin & Trahms, Annette (2019): Adult education and lifelong learning, in: Hans-Peter Blossfeld & Hans-Günther Roßbach (Ed.), *Education as a lifelong process. The German National Educational Panel Study (NEPS).* Wiesbaden: Springer VS. pp. 325–346.

Antonczyk, Dirk, Fitzenberger, Bernd & Leuschner, Ute (2009): Can a task-based approach explain the recent changes in the German wage structure? *Jahrbücher für Nationalökonomie und Statistik* 229(2-3): 214–238. https://doi.org/10.1515/jbnst-2009-2-309

Arnold, Daniel, Bellmann, Lutz, Steffes, Susanne & Wolter, Stefanie (2017): Digitalisierung am Arbeitsplatz: Wandel der Arbeitsanforderungen und -belastungen, in: Joachim Möller & Ulrich Walwei (Ed.), *Arbeitsmarkt kompakt. Analysen, Daten, Fakten.* Bielefeld: Bertelsmann. pp. 125–126.

Arntz, Melanie, Dengler, Katharina, Dorau, Ralf, Gregory, Terry, Hartwig, Matthias, Helmrich, Robert, Lehmer, Florian, Matthes, Britta, Tisch, Anita, Wischniewski, Sascha & Zierahn, Ulrich (2020 a): *Digitalisierung und Wandel der Beschäftigung (DiWaBe) – Eine Datengrundlage für die interdisziplinäre Sozialpolitikforschung*. ZEW-Dokumentation 20-02, Mannheim.

Arntz, Melanie, Gregory, Terry, Lehmer, Florian, Matthes, Britta & Zierahn, Ulrich (2016): *Arbeitswelt 4.0 – Stand der Digitalisierung in Deutschland: Dienstleister haben die Nase vorn*. IAB-Kurzbericht 22/2016, Nürnberg.

Arntz, Melanie, Gregory, Terry & Zierahn, Ulrich (2017): Revisiting the risk of automation. *Economics Letters* 159: 157–160. https://doi.org/10.1016/j.econlet.2017.07.001

Arntz, Melanie, Gregory, Terry & Zierahn, Ulrich (2020 b): Digitization and the Future of Work: Macroeconomic Consequences, in: Klaus F. Zimmermann (Ed.), *Handbook of Labor, Human Resources and Population Economics.* Wiesbaden: Springer. pp. 1–29.

Autor, David (2013): The „Task Approach“ to Labor Markets: An Overview. *Journal for Labour Market Research* 46(3): 185–199. https://doi.org/10.1007/s12651-013-0128-z

Autor, David (2015): Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives* 29(3): 3–30. https://doi.org/10.1257/jep.29.3.3

Autor, David, Levy, Frank & Murnane, Richard J. (2003): The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics* 118(4): 1279–1333. https://doi.org/10.1162/003355303322552801

Bessen, James (2016): *How Computer Automation Affects Occupations: Technology, Jobs, and Skills.* Boston University School of Law, Law and Economics Research Paper 15-49, Boston. http://dx.doi.org/10.2139/ssrn.2690435

https://doi.org/10.5771/0038-6073-2021-4-415 - am 29.01.2026, 17:11:12. https://www.inlibra.com/de/agb - Open Access -

BIBB (2017): *Durchlässigkeit im Bildungssystem. Möglichkeiten zur Gestaltung individueller Bildungswege*. Bonn. https://www.bibb.de/dienst/veroeffentlichungen/de/publication/show/8426

Black, Sandra E & Spitz-Oener, Alexandra (2010): Explaining women's success: technological change and the skill content of women's work. *The Review of Economics and Statistics* 92(1): 187–194. https://doi.org/10.1162/rest.2009.11761

Blossfeld, Hans-Peter, Roßbach, Hans-Günther & von Maurice, Jutta (2011): Education as a lifelong process. The National Educational Panel Study (NEPS). *Zeitschrift für Erziehungswissenschaft* 14(2 Supplement).

BMAS (2020): Glossar: *Der Dialogprozess Arbeiten 4.0.* https://www.bmas.de/DE/Themen/Arbeitsmarkt/Arbeiten-vier-null/arbeiten-4-0.html

BMBF (2017): Bekanntmachung: Richtlinie zur Förderung von Forschung zu "Digitalisierung im Bildungsbereich – Grundsatzfragen und Gelingensbedingungen". *Bundesanzeiger vom 26.9.2017.* https://www.bmbf.de/foerderungen/bekanntmachung-1420.html

Bonin, Holger, Gregory, Terry & Zierahn, Ulrich (2015): *Übertragung der Studie von Frey/Osborne (2013) auf Deutschland.* ZEW-Kurzexpertise 57, Mannheim.

Briken, Kendra, Chillas, Shiona, Krzywdzinski, Martin & Marks, Abigail (2017): *The New Digital Workplace. How New Technologies Revolutionise Work. Critical Perspectives on Work and Employment Series.* London: Palgrave.

Brynin, Malcolm (2006): Gender, technology and jobs. *The British Journal of Sociology* 57(3): 437–453. https://doi.org/10.1111/j.1468-4446.2006.00119.x

Brynjolfsson, Erik & McAfee, Andrew (2014): *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies.* New York: W. W. Norton & Company.

Brynjolfsson, Erik, Rock, Daniel & Syverson, Chad (2017): Artificial intelligence and the modern productivity paradox: a clash of expectations and statistics, in: Agrawal, Ajay, Gans, Joshua & Goldfarb, Avi (Ed.), *The Economics of Artificial Intelligence: An Agenda*. Chicago: University of Chicago Press. pp. 23–57.

Carretero, Stephanie, Vuorikari, Riina & Punie, Yves (2017): *DigComp 2.1: The digital competence framework for citizens with eight proficiency levels and examples of use.* EUR–Scientific and Technical Research Report. Information Society.

Cheng, Siwei, Chauhan, Bhumika & Chintala, Swati (2019): The Rise of Programming and the Stalled Gender Revolution. *Sociological Science* 6(13): 321–351. https://doi.org/10.15195/v6.a13

Chiacchio, Francesco, Petropoulos, Georgios & Pichler, David (2018): *The impact of industrial robots on EU employment and wages: A local labour market approach*. Bruegel Working Paper 2018/02.

Czaja, Sara J., Sharit, Joseph, Ownby, Raymond, Roth, David L. & Nair, Sankaran (2001): Examining age differences in performance of a complex information search and retrieval task. *Psychology and Aging* 16(4): 564–579. https://doi.org/10.1037/0882-7974.16.4.564

Damioli, Giacomo, Van Roy, Vincent & Vertesy, Daniel (2021 a): The impact of artificial intelligence on labor productivity. *Eurasian Business Review* 11(1): 1–25. https://doi.org/10.1007/s40821-020-00172-8

Damioli, Giacomo, Van Roy, Vincent, Vertesy, Daniel & Vivarelli, Marco (2021 b): *May AI revolution be labour-friendly? Some micro evidence from the supply side.* IZA Discussion Paper 14309, Bonn.

https://doi.org/10.5771/0038-6073-2021-4-415 - am 29.01.2026, 17:11:12. https://www.inlibra.com/de/agb - Open Access -

Dauth, Wolfgang, Findeisen, Sebastian, Suedekum, Jens & Woessner, Nicole (2018): *German Robots – The Impact of Industrial Robots on Workers.* CEPR discussion paper 12306, London.

Deming, David (2017): The growing importance of social skills in the labor market. *The Quarterly Journal of Economics* 132(4): 1593–1640. https://doi.org/10.1093/qje/qjx022

Dengler, Katharina & Matthes, Britta (2015): *Folgen der Digitalisierung für die Arbeitswelt: Substituierbarkeitspotenziale von Berufen in Deutschland*. IAB-Forschungsbericht 11/2015, Nürnberg.

Dengler, Katharina & Matthes, Britta (2018): The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany. *Technological Forecasting and Social Change* 137: 304–316. https://doi.org/10.1016/j.techfore.2018.09.024

Dengler, Katharina, Stops, Michael & Vicari, Basha (2016): *Occupation-Specific Matching Efficiency.* IAB-Discussion Paper 16/2016, Nürnberg.

England, Paula, Levine, Andrew & Mishel, Emma (2020): Progress toward gender equality in the United States has slowed or stalled. *Proceedings of the National Academy of Sciences* 117(13): 6990–6997. https://doi.org/10.1073/pnas.1918891117

Fregin, Marie-Christine, Levels, Mark & van der Velden, Rolf (2020): Labour market institutions and the challenge of allocating the right people to the right jobs: Evidence on the relation between labour market institutions and optimal skill matching from 28 industrial countries. *Journal of Comparative International Education* 50(2): 257–275. https://doi.org/10.1080/03057925.2019.1695197

Frey, Carl B. & Osborne, Michael (2017): The Future of Employment: How Susceptible are Jobs to Computerisation? *Technological Forecasting & Social Change* 114: 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Friedrich, Teresa S., Laible, Marie-Christine, Pollak, Reinhard, Schongen, Sebastian, Schulz, Benjamin & Vicari, Basha (2022): *Digitalisierung der Arbeitswelt – Ein neues Messinstrument für die NEPS-Erwachsenenbefragungen.* NEPS-Survey Paper 92, Bamberg.

Genz, Sabrina, Janser, Markus & Lehmer, Florian (2019): The Impact of Investments in New Digital Technologies on Wages – Worker-Level Evidence from Germany. *Journal of Economics and Statistics* 239(3): 483–521. https://doi.org/10.1515/jbnst-2017-0161

Goos, Maarten, Manning, Alan & Salomons, Anna (2014): Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review* 104(8): 2509–2526. https://doi.org/10.1257/aer.104.8.2509

Graetz, Georg & Michaels, Guy (2018): Robots at work. *Review of Economics Statistics* 100(5): 753–768. https://doi.org/10.1162/rest_a_00754

Gregory, Terry, Salomons, Anna & Zierahn, Ulrich (2016): *Racing with or against the machine? Evidence from Europe.* ZEW-Discussion Paper 16-053, Mannheim.

Helsper, Ellen J. & Eynon, Rebecca (2010): Digital natives: where is the evidence? *British Educational Research Journal* 36(3): 503–520. https://doi.org/10.1080/01411920902989227

Hill, Catherine, Corbett, Christianne & St. Rose, Andresse (2010): *Why so few women in science, technology, engineering, and mathematics.* Washington, DC: American Association of University Women.

Hipp, Lena (2019): Insecure times? Workers' perceived job and labor market security in 23 OECD countries. *Social Science Research* 60(1): 1–14. https://doi.org/10.1016/j.ssresearch.2016.04.004

https://doi.org/10.5771/0038-6073-2021-4-415 - am 29.01.2026, 17:11:12. https://www.inlibra.com/de/agb - Open Access -

Hirsch-Kreinsen, Hartmut (2015): Einleitung: Digitalisierung industrieller Arbeit, in: Hartmut Hirsch-Kreinsen, Peter Ittermann & Jonathan Niehaus (Ed.), *Digitalisierung industrieller Arbeit.* Baden-Baden: Nomos. pp. 10–31.

Korupp, Sylvia E. & Szydlik, Marc (2005): Causes and Trends of the Digital Divide. *European Sociological Review* 21(4): 409–422. https://doi.org/10.1093/esr/jci030

Korupp, Sylvia E., Kühnemund, Harald & Schupp, Jürgen (2006): *Digitale Spaltung in Deutschland. Geringere Bildung – seltener am PC*. DIW Wochenbericht 19/2006, Berlin.

Kristal, Tali (2020): Why Has Computerization Increased Wage Inequality? Information, Occupational Structural Power, and Wage Inequality. *Work and Occupations* 47(4): 466–503. https://doi.org/10.1177/0730888420941031

Matthes, Britta, Christoph, Bernhard, Janik, Florian & Ruland, Michael (2014): Collecting information on job tasks—an instrument to measure tasks required at the workplace in a multi-topic survey. *Journal for Labour Market Research* 47(4): 273–297. https://doi.org/10.1007/s12651-014-0155-4

Mauno, Saija, Minkkinen, Jaana, Tsupari, Heidi, Huhtala, Mari & Feldt, Taru (2019): Do Older Employees Suffer More from Work Intensification and Other Intensified Job Demands? Evidence from Upper White-Collar Workers. *Scandinavian Journal of Work and Organizational Psychology* 4(1): 1–13. https://doi.org/10.16993/sjwop.60

Mayer, Claude-Hélène (2020): Key concepts for managing organizations and employees turning towards the Fourth Industrial Revolution. *International Review of Psychiatry* 32(7-8): 673–684. https://doi.org/10.1080/09540261.2020.1803220

Nedelkoska, Ljubica & Quintini, Glenda (2018): *Automation, skills use and training.* OECD Social, Employment and Migration Working Papers 202, Paris. https://doi.org/10.1787/1815199X

Neves, Barbara Barbosa & Mead, Geoffrey (2020): Digital Technology and Older People: Towards a Sociological Approach to Technology Adoption in Later Life. *Sociology* 55(5): 888–905. https://doi.org/10.1177/0038038520975587

Pfeiffer, Sabine (2018): Technisierung von Arbeit, in: Fritz Böhle, Günter G. Voß & Günther Wachtler (Ed.), *Handbuch Arbeitssoziologie. Band 1: Arbeit, Strukturen, Prozesse.* 2. Auflage. Wiesbaden: Springer. pp. 321–358.

Pfeiffer, Sabine (2019): Digitale Arbeitswelten und Arbeitsbeziehungen: What you see is what you get? *Industrielle Beziehungen* 26: 232–249. https://doi.org/10.3224/indbez.v26i2.07

Pouliakas, Konstantinos (2018): *Determinants of automation risk in the EU labour market: A skills-needs approach.* IZA Discussion Paper 11829, Bonn.

Senkbeil, Martin & Ihme, Jan M. (2015): *NEPS Technical Report for Computer Literacy: Scaling results of Starting Cohort 6–Adults.* NEPS-Working Paper 61, Bamberg.

Spitz-Oener, Alexandra (2006): Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics* 24(2): 235–270. https://doi.org/10.1086/499972

Weinberg, Bruce A. (2000): Computer use and the demand for female workers. *ILR Review* 53(2): 290–308. https://doi.org/10.1177/001979390005300206

Wirtz, Jochen, Patterson, Paul G., Kunz, Werner H., Gruber, Thorsten, Vinh Nhat, Lu, Paluch, Stefanie & Martins, Antje (2018): Brave New World: Service Robots in the Frontline. *Journal of Service Management* 29(5): 907–931. https://doi.org/10.1108/JOSM-04-2018-0119

https://doi.org/10.5771/0038-6073-2021-4-415 - am 29.01.2026, 17:11:12. https://www.inlibra.com/de/agb - Open Access -

Appendix

Table A1: Dimensions, items, and their intentions

Dimension	Item	Intention
D1: Perpetuation of networked digital technologies and automation	The topic "digitalization of the working world" is much discussed today. But not the entire working world is equally affected by digitalization. Many jobs remain unchanged. It is important for us to find out how!!you!! experience digitalization. An important aspect of this is the use of networked digital technologies!!at work!!. Some examples are online platforms, e-mails, tablets, cloud services and self-controlling or self-learning computer systems.	Introduces topic and gives definition.
	Networked/SUF: th60001 We are interested in your assessment of your occupation. How strongly is your job as <preload_job> characterized by the use of networked digital technologies? 1: very strongly 2: strongly 3: partly strongly 4: barely 5: not at all	Captures the dimension “networked digital technologies” (in contrast to “automation”). Two questions are needed as networked digital technologies and automation are two different dimensions. Subjective assessment of extent of digitalization at job.
	Activity change/SUF: th60002 If you compare your job as < preload_job > today and two years ago, you are using networked digital technologies today... 1: much more frequently 2: more frequently 3: slightly more frequently 4: bout equally frequently 5: less frequently 6: not employed two years ago Do not read aloud: If the respondent has changed his/her job in the last two years, compare the position two years ago with the current one. If the respondent was not employed two years ago, please select "not employed two years ago".	Subjective perception of changes in the use of networked digital technologies.

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Dimension	Item	Intention
	Automation/SUF: th60007 So far, our questions about digitalization have mainly concerned the use of networked digital technologies. But we are also interested in another aspect:!!the automation of work processes!! By this we mean the use of computer systems that determine, evaluate or optimize work processes mostly independently by making their own decisions. What about your work? To what extent are the work processes at!!your workplace!! automatized? 1: very strongly 2: strongly 3: partly strongly 4: barely 5: not at all	Captures the dimension "automation" (in contrast to "networked digital technologies").
D2: Qualification needs	Further training needs/SUF: th60003 In the following, I will read some statements to you. To what extent do these statements apply to your job as < preload_job >? In my job, networked digital technologies require a constant development of my skills. Does the statement apply to you completely, rather apply, partly apply, rather not apply or not apply at all? 1: does apply completely 2: does rather apply 3: does partly apply 4: does rather not apply 5: does not apply at all 6: no use of networked digital technologies	Requirements for lifelong learning resulting from networked digital technologies.
	Prepared/SUF: th60004 Thanks to my skills, I feel well prepared for working with networked digital technologies. Does the statement apply to you completely, rather apply, partly apply, rather not apply or not apply at all? 1: does apply completely 2: does rather apply 3: does partly apply 4: does rather not apply 5: does not apply at all 6: no use of networked digital technologies	Ability to use networked digital technologies.

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Dimension	Item	Intention
D3: Affective impact of digitalization	Feeling controlled/SUF: th60005 In my job, I feel increasingly controlled by networked digital technologies. Does the statement apply to you completely, rather apply, partly apply, rather not apply or not apply at all? 1: does apply completely 2: does rather apply 3: does partly apply 4: does rather not apply 5: does not apply at all 6: no use of networked digital technologies	Feeling of heteronomy can have two sources: Technology and humans (in terms of monitoring). Both sources are valid for question.
	Information quantity/SUF: th60006 In my job, I often receive too much information at once through networked digital technologies. Does the statement apply to you completely, rather apply, partly apply, rather not apply or not apply at all? 1: does apply completely 2: does rather apply 3: does partly apply 4: does rather not apply 5: does not apply at all 6: no use of networked digital technologies	Feeling of mental overload due to information overload.

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Dimension	Item	Intention
D4: Use of networked digital technologies	Information search_1/SUF: th6011 a Now we are interested in what you do in your job as < preload_job > exactly. Do you use the internet or intranet to search for information? 1: yes 2: no	Dimension 4 captures the objective extent of digitalization at a job. Note that the questions in D4 come in pairs. The second question in the pair is only asked if the respondent answered yes to the first question. A stopping criteria filters to the next dimension when respondents answered no three times. Following Carretero et al. (2017), the complexity of the use of specific technologies increases with each question pair
	Information search_2/SUF: th6011 b How often do you use the internet or intranet to search for information in a typical working week? 1: several times a day 2: daily 3: several times a week 4: once a week 5: less frequently	Complexity: Simple tasks.
	File modification_1/SUF: th6012 a Do you create or edit digital files in your job? 1: yes 2: no 'Digital files' are, for example, text or image files that can only be edited using computers, tablets, etc.	Complexity: Well-defined and routine tasks, and straightforward problems.
	File modification_2/SUF: th6012 b How often do you create or edit digital files in a typical working week? 1: several times a day 2: daily 3: several times a week 4: once a week 5: less frequently If a file is edited throughout the day, select several times a day.	

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Dimension	Item	Intention
	Exchange_1/SUF: th6013 a Do you exchange files with other people using networked digital technologies? (An example of file sharing via networked digital technologies is the use of e-mail, internal data servers or cloud systems). 1: yes 2: no	Complexity: Tasks, and well-defined and non-routine problems.
	Exchange_2/SUF: th6013 b How often do you exchange files with other people in a typical working week? 1: several times a day 2: daily 3: several times a week 4: once a week 5: less frequently	
	Internet presence_1/SUF: th6014 a Do you maintain websites in your job? (An example of maintaining websites is the updating of social media content, or the technical modification of websites, for example via content management systems.) 1: yes 2: no	Complexity: Different tasks and problems.
	Internet presence_2/SUF: th6014 b How often do you maintain websites in a typical working week? 1: several times a day 2: daily 3: several times a week 4: once a week 5: less frequently	
	Websites_1/SUF: th6015 a Do you create new websites in your job? 1: yes 2: no The creation of websites includes the technical redesign and initial programming of websites, not just the maintenance.	Complexity: Different tasks and problems

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Dimension	Item	Intention
	Websites_2/SUF: th6015 b How often do you create new websites in a typical working week? 1: several times a day 2: daily 3: several times a week 4: once a week 5: less frequently	
	Algorithms_1/SUF: th6016 a Do you program algorithms for intelligent systems in your job? 1: yes 2: no	Complexity: Resolve complex problems with many interacting factors
	Algorithms_2/SUF: th6016 b How often do you program algorithms for intelligent systems in a typical working week? 1: several times a day 2: daily 3: several times a week 4: once a week 5: less frequently	
D5: Labor Market Prospects	Job loss/SUF: th60008 We are now interested in your assessment of the consequences of digitalization. How much has this development changed the risk of losing your current job? Does the risk increase strongly, increase slightly, stay about the same, decrease slightly or decrease strongly? 1: does increase strongly 2: does increase slightly 3: does stay about the same 4: does decrease slightly 5: does decrease strongly	Subjective risk to loose current job due to digital technologies and automation.

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Dimension	Item	Intention
	Labor market chances/SUF: th60009 And if you don't think of your current job, but of!! your!! skills and chances in the labor market in general: How do you assess your chances of finding a new job in a labor market changed by digitalization? Would your chances improve strongly, improve, stay the same, worsen or worsen strongly? 1: improve strongly 2: improve 3: stay the same 4: worsen 5: worsen strongly	Subjective assessment of chances due to respondents' ability and skills and their match with a digitalized workplace.

Table A2: Descriptive statistics with the total sample

	min	max	mean	sd	skewness	N	-20 (system)	-97 (refuse)	-98 (do not know)
Networked	1	5	2.63	1.22	0.30	5.103	0.00%	0.00%	0.04%
Activity change	1	5	3.10	1.14	-0.22	5.017	1.12%	0.06%	0.55%
Further training needs	1	5	2.82	1.17	0.17	4.994	2.08%	0.00%	0.10%
Prepared	1	5	2.79	1.09	0.24	4.979	2.39%	0.00%	0.08%
Feeling controlled	1	5	3.71	1.04	-0.55	4.968	2.59%	0.00%	0.10%
Information quantity	1	5	3.40	1.15	-0.31	4.959	2.80%	0.02%	0.04%
Information search_1	0	1	0.83	0.38	-1.73	5.105	0.00%	0.00%	0.00%
Information search_2	1	5	1.85	1.12	1.18	4.219	17.32%	0.00%	0.04%
File modification_1	0	1	0.62	0.48	-0.51	5.103	0.00%	0.00%	0.04%
File modification_2	1	5	1.97	1.20	1.01	3.187	37.57%	0.00%	0.00%
Exchange_1	0	1	0.74	0.44	-1.10	5.104	0.00%	0.00%	0.02%
Exchange_2	1	5	1.99	1.24	1.01	3.785	25.86%	0.00%	0.00%
Internet presence_1	0	1	0.17	0.38	1.76	4.422	13.38%	0.00%	0.00%
Internet presence_2	1	5	3.80	1.28	-0.79	749	85.33%	0.00%	0.00%
Websites_1	0	1	0.04	0.20	4.56	4.421	13.38%	0.00%	0.02%
Websites_2	1	5	4.40	1.03	-1.89	186	96.36%	0.00%	0.00%
Algorithms_1	0	1	0.03	0.17	5.37	4.422	13.38%	0.00%	0.00%
Algorithms_2	1	5	3.18	1.50	-0.23	139	97.28%	0.00%	0.00%
Automation	1	5	3.96	1.05	-0.81	5.097	0.00%	0.02%	0.14%
Job loss	1	5	3.24	0.87	0.63	5.003	0.00%	0.22%	1.78%
Labor market chances	1	5	3.16	0.83	0.21	5.013	0.00%	0.29%	1.51%

Source: Authors' own calculations based on the NEPS-SC6 wave 12.

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Table A3: Descriptive statistics with the analysis sample

	min	max	mean	sd	skewness	N
Networked	1	5	2.55	1.15	0.30	4694
Activity change	1	5	3.04	1.12	-0.20	4694
Further training needs	1	5	2.77	1.14	0.18	4694
Prepared	1	5	2.77	1.07	0.24	4694
Feeling controlled	1	5	3.69	1.04	-0.53	4694
Information quantity	1	5	3.37	1.15	-0.29	4694
Information search_1	0	1	0.85	0.35	-1.99	4694
Information search_2	1	5	1.82	1.09	1.22	4001
File modification_1	0	1	0.65	0.48	-0.63	4694
File modification_2	1	5	1.95	1.18	1.04	3050
Exchange_1	0	1	0.77	0.42	-1.28	4694
Exchange_2	1	5	1.96	1.22	1.05	3612
Internet presence_1	0	1	0.17	0.38	1.74	4187
Internet presence_2	1	5	3.81	1.27	-0.79	720
Websites_1	0	1	0.04	0.20	4.54	4187
Websites_2	1	5	4.41	1.03	-1.96	178
Algorithms_1	0	1	0.03	0.18	5.34	4187
Algorithms_2	1	5	3.20	1.49	-0.24	133
Automation	1	5	3.92	1.05	-0.76	4694
Job loss	1	5	3.23	0.87	0.62	4694
Labor market chances	1	5	3.15	0.82	0.19	4694

Source: Authors' own calculations based on the NEPS-SC6 wave 12.

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Table A4: Timestamp analyses

	Dimension 1 a	Dimension 1 b	Dimension 2	Dimension 3	Dimension 5
Female	t(4621) = -2.16, p=.0307	t(4617) = -1.60, p=.1098	t(4622) = -4.33, p<.001	t(4649) = 0.17, p=.8636	t(4394.45) = -6.00, p<.001
Age	F(3, 1791.8) = 2.50, p=.0578	F(1, 4617) = 0.09, p=.767	F(1, 4622) = 1.10, p=.295	F(1, 4649) =28.11, p<.001	F(3,1859.4) = 27.65, p<.001
Education	F(1, 4621) = 5.26, p=.0219	F(1, 4617) = 1.24, p=.265	F(1, 4622) = 0.01, p=.941	F(1, 4649) = 0.26, p=.61	F(1, 4617) = 5.36, p=.0206
Analytic	t(4621) = 4.12, p<.001	t(4617) = 0.89, p=.3692	t(4622) = 2.58, p=.0098	t(4649) = -0.14, p=.8901	t(4617) = 1.72, p=.0854
Interactive	t(4621) = 0.64, p=.5246	t(4617) = -1.38, p=.1662	t(4622) = -0.27, p=.7892	t(4649) = -0.48, p=.6278	t(4493.69) = -2.14, p=.0326
Manual	t(4621) = -0.04, p=.9713	t(4617) = 0.90, p=.3739	t(4622) = -0.25, p=.8045	t(4649) = 1.48, p=.1383	t(4506.51) = -2.88, p=.0040
Routine	t(4099.28) = -4.09, p<.001	t(4617) = 1.36, p=.1749	t(4622) = -1.32, p=.1855	t(4649) = 0.24, p=.8131	t(4617) = -1.77, p=.0766
Autonomy	t(4621) = 1.47, p=.1409	t(4617) = -0.58, p=.5620	t(4622) = 0.66, p=.5089	t(4649) = -1.47, p=.1422	t(4617) = -0.21, p=.8362

Source: Authors' own calculations based on the NEPS-SC6 wave 12.

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Table A5: Linear regression models on all digitalization items as dependent variable using gender, age, and education

	M1 Networked	M2 Automation	M3 Activity Change	M4 Further Training Needs	M5 Prepared	M6 Feeling controlled	M7 Information quantity	M8 Index use	M9 Job loss	M10 Labor market chances
Female	-.243***	-.111***	-.036	-.197***	-.309***	.022	-.134***	-.288***	.021	-.167***
	(.033)	(.031)	(.033)	(.033)	(.031)	(.031)	(.034)	(.033)	(.026)	(.023)
Age	-.012***	-.008***	-.008***	-.006***	-.012***	.005***	.002	-.015***	-.001	-.021***
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.001)	(.001)
No voc. training	.325***	-.057	-.074	.221*	.196*	-.108	.054	.502***	-.039	.113+
	(.089)	(.084)	(.089)	(.089)	(.083)	(.083)	(.091)	(.090)	(.069)	(.063)
CSE (RS) + voc. training	.445***	.038	.299***	.381***	.373***	.126*	.328***	.659***	.015	.126***
	(.056)	(.053)	(.056)	(.057)	(.052)	(.052)	(.058)	(.057)	(.044)	(.040)
A Levels + voc. training	.684***	-.037	.380***	.598***	.548***	.048	.387***	1.137***	.059	.178***
	(.061)	(.057)	(.061)	(.061)	(.056)	(.056)	(.062)	(.062)	(.047)	(.043)
University degree	.778***	-.180***	.375***	.656***	.596***	-.026	.470***	1.562***	.027	.279***
	(.055)	(.052)	(.055)	(.055)	(.051)	(.051)	(.056)	(.056)	(.043)	(.039)
Constant	3.666***	2.610***	3.117***	3.205***	3.612***	1.979***	2.254***	2.487***	2.798***	3.887***
	(.115)	(.109)	(.115)	(.116)	(.107)	(.107)	(.118)	(.117)	(.090)	(.081)
Observations	4694	4694	4694	4694	4694	4694	4694	4694	4694	4694
R^2	.073	.012	.022	.048	.069	.007	.021	.213	.001	.083

Note: + p <.1, * p <.05, ** p <.01, *** p <.001. Standard errors in brackets. Higher values on the dependent variable indicate higher agreement or frequency. Each column represents one model using a different digitalization item as dependent variable. The digitalization item is indicated by each model title. The reference category for each education variable is "CSE (HS) + vocational training".
Source: Authors' own calculations based on the NEPS-SC6 wave 12.

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Table A6: Linear regression models on all digitalization items as dependent variable including job tasks

	M1 Networked	M2 Automation	M3 Activity Change	M4 Further Training Needs	M5 Prepared	M6 Feeling controlled	M7 Information quantity	M8 Index use	M9 Job loss	M10 Labor market chances
Female	-.170***	-.108***	-.018	-.104***	-.244***	.020	-.071*	-.150***	-.010	-.124***
	(.031)	(.032)	(.033)	(.031)	(.030)	(.031)	(.034)	(.029)	(.027)	(.024)
Age	-.007***	-.005***	-.004*	.000	-.010***	.009***	.006***	-.013***	-.001	-.020***
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.001)	(.001)
No voc. training	.116	-.107	-.182*	.031	.002	-.126	-.074	.180*	-.054	.051
	(.080)	(.083)	(.086)	(.080)	(.077)	(.082)	(.087)	(.075)	(.069)	(.062)
CSE (RS) + voc. training	.146***	-.041	.102+	.071	.127*	.040	.113*	.248***	-.009	.042
	(.052)	(.053)	(.055)	(.051)	(.049)	(.053)	(.056)	(.048)	(.045)	(.040)
A Levels + voc. training	.145*	-.172***	.034	.049	.086	-.083	.010	.367***	.020	.019
	(.058)	(.060)	(.062)	(.057)	(.055)	(.059)	(.063)	(.054)	(.050)	(.044)
University degree	-.002	-.378***	-.118*	-.147***	-.058	-.226***	-.084	.464***	-.022	.050
	(.056)	(.058)	(.060)	(.056)	(.054)	(.057)	(.061)	(.053)	(.049)	(.043)
Analytic	.899***	.070	.492***	.942***	.782***	.171+	.793***	1.850***	-.096	.285***
	(.093)	(.096)	(.099)	(.092)	(.089)	(.094)	(.101)	(.087)	(.080)	(.071)
Routine	-1.650***	-.768***	-.923***	-1.944***	-.964***	-.774***	-1.148***	-.878***	-.112	-.458***
	(.094)	(.097)	(.101)	(.093)	(.090)	(.096)	(.102)	(.088)	(.081)	(.072)
Manual	-1.153***	-.538***	-.385***	-.698***	-.953***	-.075	-.458***	-1.195***	-.353***	-.096*
	(.062)	(.064)	(.066)	(.061)	(.059)	(.063)	(.067)	(.058)	(.053)	(.047)
Autonomy	-.010	-.261***	-.104	.070	.388***	-.480***	-.089	.731***	-.255***	.321***
	(.071)	(.073)	(.076)	(.070)	(.067)	(.072)	(.077)	(.066)	(.061)	(.054)
Interactive	-.136+	-.254***	.692***	.253***	-.052	.405***	.257***	.230***	.005	.058
	(.079)	(.081)	(.084)	(.078)	(.075)	(.080)	(.085)	(.074)	(.068)	(.061)
Constant	4.451***	3.319***	3.196***	3.667***	3.913***	2.263***	2.452***	2.122***	3.170***	3.802***
	(.133)	(.137)	(.142)	(.131)	(.126)	(.135)	(.144)	(.124)	(.114)	(.102)
Observations	4694	4694	4694	4694	4694	4694	4694	4694	4694	4694
R^2	.255	.045	.100	.255	.209	.045	.111	.459	.014	.123

Note: + p <.1, * p <.05, ** p <.01, *** p <.001. Standard errors in brackets. Higher values on the dependent variable indicate higher agreement or frequency. Each column represents one model using a different digitalization item as dependent variable. The digitalization item is indicated by each model title. The reference category for each education variable is "CSE (HS) + vocational training".
Source: Authors' own calculations based on the NEPS-SC6 wave 12.

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Table A7: Linear regression models on the number of further training courses using digitalization items as explanatory variables

	M1 Networked	M2 Automation	M3 Activity Change	M4 Further Training Needs	M5 Prepared	M6 Feeling controlled	M7 Information quantity	M8 Index use	M9 Job loss	M10 Labor market chances
Digitalization Item	.105***	.021	.130***	.178***	.096***	.071***	.083***	.112***	-.037	.099***
	(.018)	(.019)	(.018)	(.018)	(.019)	(.019)	(.018)	(.018)	(.023)	(.025)
Female	.330***	.306***	.310***	.341***	.334***	.303***	.316***	.337***	.304***	.321***
	(.041)	(.041)	(.040)	(.040)	(.041)	(.041)	(.041)	(.041)	(.041)	(.041)
Age	.107***	.114***	.105***	.095***	.115***	.107***	.107***	.108***	.116***	.115***
	(.021)	(.021)	(.021)	(.021)	(.021)	(.021)	(.021)	(.021)	(.021)	(.021)
Age^2	-.001***	-.001***	-.001***	-.001***	-.001***	-.001***	-.001***	-.001***	-.001***	-.001***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
No voc. training	.039	.073	.083	.036	.053	.081	.069	.017	.070	.061
	(.109)	(.109)	(.109)	(.108)	(.109)	(.109)	(.109)	(.109)	(.109)	(.109)
CSE (RS) + voc. training	.169*	.213***	.177*	.150*	.178*	.206***	.188***	.142*	.214***	.202***
	(.070)	(.069)	(.069)	(.069)	(.070)	(.069)	(.069)	(.070)	(.069)	(.069)
A Levels + voc. training	.313***	.385***	.336***	.280***	.331***	.381***	.353***	.257***	.386***	.366***
	(.075)	(.075)	(.075)	(.075)	(.075)	(.075)	(.075)	(.077)	(.075)	(.075)
University degree	.469***	.555***	.502***	.434***	.494***	.553***	.512***	.375***	.552***	.523***
	(.069)	(.068)	(.068)	(.068)	(.069)	(.068)	(.068)	(.073)	(.068)	(.068)
Constant	-2.579***	-2.454***	-2.548***	-2.460***	-2.727***	-2.380***	-2.414***	-2.488***	-2.342***	-2.747***
	(.555)	(.557)	(.554)	(.550)	(.558)	(.556)	(.555)	(.554)	(.558)	(.562)
Observations	4694	4694	4694	4694	4694	4694	4694	4694	4694	4694
R^2	.046	.039	.049	.059	.044	.041	.043	.047	.039	.042

Note: + p <.1, * p <.05, ** p <.01, *** p <.001. Standard errors in brackets. Higher values on the digitalization variable indicate higher agreement or frequency. Each column represents one model using a different digitalization item as explanatory variable. The digitalization item is indicated by each model title. The reference category for each education variable is “CSE (HS) + vocational training”.
Source: Authors’ own calculations based on the NEPS-SC6 wave 12.

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