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Research Report

Measuring Task-Based Advanced Automation Technologies & Digital Assistance Systems in the National Educational Panel Study

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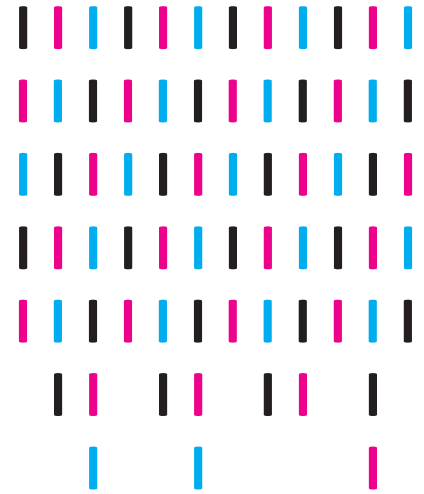
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NEPS SURVEY PAPERS

Alexander Dicks, Martin Ehlert, Insa Grüttgen,
Benjamin Schulz and Basha Vicari

MEASURING TASK-BASED ADVANCED AUTOMATION TECHNOLOGIES & DIGITAL ASSISTANCE SYSTEMS IN THE NATIONAL EDUCATIONAL PANEL STUDY

NEPS Survey Paper No. 128
Bamberg, April 2026

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The NEPS *Survey Paper* series provides articles with a focus on methodological aspects and data handling issues related to the German National Educational Panel Study (NEPS).

They are of particular relevance for the analysis of NEPS data as they describe data editing and data collection procedures as well as instruments or tests used in the NEPS survey. Papers that appear in this series fall into the category of 'grey literature' and may also appear elsewhere.

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Measuring Task-Based Advanced Automation Technologies & Digital Assistance Systems in the National Educational Panel Study

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This paper uses data from the National Educational Panel Study (NEPS; see Blossfeld & Roßbach, 2019). The NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi, Germany) in cooperation with a nationwide network.

Measuring Task-Based Advanced Automation Technologies & Digital Assistance Systems in the National Educational Panel Study

Abstract

We introduce a new task-based instrument for the measurement of automation at the workplace. We refer to the automation technologies as “digital assistance systems”, which we define as advanced automation systems such as software and devices that automatically complete tasks to support workers. They include artificial intelligence chatbots, image and video creation algorithms, predictive maintenance and analysis tools, digital instructions systems as well as wearable technologies and collaborative robots. Drawing on the task-based approach and recognizing recent technological advancements, we developed seven items capturing various types of digital assistance systems for the National Educational Panel Study (NEPS). Results from NEPS Starting Cohorts 4 and 6 show that usage varies by age, education level and correlates with complementary job tasks as well as measures of workplace digitalization. The instrument complements existing NEPS items on workplace digitalization and offers potential for longitudinal analysis of technological change in the workplace and its impact on skill requirements, inequality, and life-long learning.

Keywords

automation, artificial intelligence, workplace technology, task-based approach

1. Introduction

The pace of workplace digitalization is accelerating with the emergence of new technologies. Strengthened by advances in computing power and the availability of big data, machine learning has made it possible to automate a wide range of work processes (Frey & Osborne, 2017; Brynjolfsson & McAfee, 2012). This trend now extends to cognitive tasks, including text comprehension and generation through large language model powered chatbots, as well as image interpretation and creation. In particular, generative artificial intelligence has recently attracted significant attention. Meanwhile, progress in sensor technology and robotics is extending automation to various manual tasks, especially when combined with machine learning. The rapid proliferation of these technologies has the potential to fundamentally reshape the employment landscape (Lane & Saint-Martin, 2021), transforming job roles, altering skill requirements, and potentially deepening labor market inequalities (Reimann et al., 2020). However, little is known about the micro-level mechanisms, such as how and which workers use these systems and the potential effects on employment quality and security, skill use, and further training needs. In particular, longitudinal data are lacking. To more precisely capture this aspect of automation through digital assistance systems, we propose new survey items grounded in the task-based approach (Autor et al., 2003; Spitz-Oener, 2006). We have developed these items for deployment in the German National Educational Panel Study (NEPS), a long-running longitudinal survey, which offers many high-quality measures of the aforementioned issues.

Broadly speaking, there are three main perspectives on how digitalization and automation may affect qualification requirements and, consequently, labor market inequality (Martinaitis et al., 2021). The first is the “deskilling” hypothesis, which posits that new technologies will replace many work tasks, leaving employees with highly standardized activities and thereby reducing qualification requirements across the board. This view traces back to Harry Braverman’s ([1974] 1998) analysis of Taylorism, which argues that it would systematically erode workers’ skills. In contrast, the “upskilling” hypothesis suggests that technological advances create new jobs with higher qualification demands or expand the skill requirements of existing roles. This view forms the core of the Skill-Biased Technological Change (SBTC) framework (Acemoglu, 2002; Autor et al., 2003). Finally, both processes may occur simultaneously but affect different segments of the labor market. According to the “polarization” thesis, digitalization automates routine, rule-based tasks, which are often found in traditional middle-class occupations. At the same time, there is an increasing demand for hard to automate low-skilled manual service work and high-skilled roles that complement new technologies (Autor & Dorn, 2013).

While some studies have examined the consequences of these trends at the macro level (e.g., Oesch & Piccitto, 2019; Martinaitis et al., 2021), an increasing number of studies now focus on measuring how digitalization is transforming the world of work at the micro level (e.g., Spitz-Oener, 2006; Matthes et al., 2014; Reimann & Tisch, 2021). The National Educational Panel Study (NEPS) already includes a module on the “*Digitalization of the World of Work*” (Friedrich et al., 2022), which primarily captures “upskilling” technologies that correlate positively with education and training. However, the study lacks detailed measures of the use of potentially “deskilling” technologies.

Our work builds on the framework for measuring AI use in the workplace developed by Giering and Kirchner (2021) for the SOEP Innovation Sample 2019 (Fedorets et al., 2022; SOEP-IS Group, 2021), which focused on four AI-related tasks: speech recognition, image recognition, text recognition, and answering domain-specific questions. They approach the measurement of AI use without requiring respondents to have explicit knowledge of the underlying technologies (see also Giering et al., 2021). We extend this framework by incorporating not only manual tasks but also the *generative* aspect of recent AI systems.

2. Theoretical background and definition

We define the technologies under investigation as “digital assistance systems”, which are digital technologies that support work by automatically performing certain tasks. The specific underlying technology (e.g., “AI”, large-language model, machine learning) is not our focus, as most users may not accurately identify or understand these aspects. The crucial factor is that these systems intervene in, replace, or supplement work processes by automatically executing certain activities or generating output. Our definition encompasses both software applications for cognitive tasks, such as text recognition (as in Giering and Kirchner 2021), and physical devices for manual tasks, like wearables or robot arms (as described by Krzywdzinski et al. 2022). Specifically, Items 1 through 4 (Text/Speech, Images/Videos, Knowledge, Data/Diagnoses) are further developments of the SOEP-IS items (Giering & Kirchner, 2021; Fedorets et al., 2022). Item 5 (Instructions) draws on the SOEP-IS and the LEEP-B3 study (Reimann et al., 2020; Gensler & Abendroth, 2021). Items 6 (Wearables) and 7 (Cobots) are original developments for this instrument.

The conceptualization of digital assistance systems is firmly grounded in the “task-based approach” model (Autor et al. 2003; Spitz-Oener 2006), which categorizes work activities along the dimensions of cognitive or manual, and routine or non-routine tasks. This framework, complemented by recent literature on artificial intelligence in the workplace (Hecker et al. 2017; Wang et al. 2021; Kelly et al. 2019; Lukanova & Ilieva 2019), provides a comprehensive lens through which to understand the diverse applications of digital assistance systems across various workplace contexts.

Building on the task-based approach, we categorize digital assistance systems into several key areas:

- Text/Speech systems support analytical tasks involving reading and writing. They automatically summarize long texts, create tables, and generate program code. LLM-based chatbots exemplify this category but also advanced language translation and grammar editing applications.
- Image/Video systems leverage recent advances in machine learning and create images, photos, graphics, and videos typically based on user input in a chat interface.
- Knowledge systems answer user’s questions and provide specialized knowledge and information based on big databases.
- Data Preparation and Diagnosis systems support analytical and decision-making processes, for example through predictive maintenance, preparing data, and making diagnoses.

- Instruction systems deliver work instructions through devices like tablets or other notifications, such as worker assistance systems, which guide workers through tasks with step-by-step interactive instructions.
- Wearables: We define these as body-worn devices, displays, and scanners.
- Collaborative Robots (Cobots): We identify these as designed for human-robot collaboration, primarily in manufacturing and medical settings.

This categorization reflects our understanding of the multifaceted nature of digital assistance systems and their transformative potential across different sectors and skill levels. The task-based framework provides a basis for examining how the emergence of these technologies affects workers differently, depending on the task content and skill profile of their activities. This approach offers the flexibility necessary to develop and formulate survey items on rapidly evolving technology and even for technologies that might not even exist yet. By refraining from the use of brand names and applications in the questions, the items can also be used unchanged for a longer time in the panel, thus improving comparability across the waves. In fact, when the framework was conceived and the survey items were formulated in early 2022, the mainstream breakthrough of LLMs with the release of ChatGPT in late 2022 had not happened yet. We believe that our framework can cover many of the applications that these services are used for. To give the reader an idea, which commercial products exemplify the different digital assistance systems, Table 1 lists some examples.

Table 1: Application and current commercial examples of digital assistance systems based on own research.

Item	Current Examples (non-exhaustive)
Text/Speech	ChatGPT*, DeepL, Google Translate
Images/Videos	Midjourney, Dall-E, Adobe Firefly
Knowledge/Information	ChatGPT*, Perplexity
Data/Diagnoses	ADA health, Tableau
Instructions	Worker assistance systems, Tablets, Data glasses (VR/AR)
Wearables	Data glasses (VR/AR), Smart watches, Gloves, Scanners
Cobots	ABB, KUKA, Omron, Universal Robots

*Due to the development of ChatGPT (and similar services like Anthropic's Claude, Google's Gemini, Microsoft's Copilot) from purely text-based chatbots to multimodal assistants, the assignment is not always clear-cut.

2.1. Possible research questions and expected relationships

The prevalence of digital assistance systems in the workplace remains underexplored, and precise data on their adoption rates are still scarce. Therefore, our primary research question addresses the extent to which these systems have penetrated the world of work. Given their rapid advancement, we anticipate a significant increase in the adoption of these systems over a short period. The inclusion of new items in NEPS will allow us to track this trend.

A subsequent question concerns the demographic and occupational characteristics of employees utilizing these systems. Unlike traditional computer use, we expect that certain digital assistance systems may be predominantly or equally prevalent among low-skilled workers and in production settings. This approach allows us to more comprehensively map

the penetration of digital assistance systems across the workforce, including employee groups who may not directly perceive their work as being influenced by computers or AI. It is expected that digital assistance systems supporting cognitive work would be more prevalent among the more educated, while those supporting manual work would be more prevalent among the less educated.

We would further expect that the use and consequences of the use of these systems differ significantly between “early adopters” and those who encounter the technologies after they have spread more widely. In particular, it is unclear whether and for which employee groups which digital assistance systems lead to “upskilling” or “downskilling”. This could be measured by changes in the composition of employee’s job tasks or by changes in skill mismatch, which are both recorded in NEPS. “Upskilling” through assistance systems can possibly lead to increased training needs. “Downskilling” could initially reduce training needs, but increase them in the long term if employees leave these jobs.

Another question concerns the effects of digital assistance systems on job quality. In principle, employees seem to respond positively to the use of assistance systems in production (Krzywdzinski et al. 2022). There also seem to be no negative effects on perceived work autonomy (Giering and Kirchner 2021). However, this relationship may depend on the type of assistance system and the workers’ educational level (Gensler and Abendroth 2021). For instance, we expect systems like text or image recognition to largely support or replace certain tasks. However, these systems can have very different effects than systems that intervene and steer workers, such as wearables or worker assistance systems. To date, existing research has relied predominantly on cross-sectional data to examine these relationships. The NEPS panel data would allow for better estimation of causality between digital systems and job quality.

3. Presentation of the construct

We first formulated the survey items in early 2022 with the goal to measure the frequency of digital assistance systems use for various tasks. The questions are preceded by an introduction text, which underlines the special nature of digital assistance systems as newer digital technologies that can support and automate work. The items are structured by task dimensions: text/language, images/videos, specialized knowledge, data/diagnoses, work instructions, wearables, and robots/cobots. To test the validity and quality of the developed questions, a cognitive pretest and a CATI pilot study were conducted in December 2022. Additionally, the expertise of colleagues from the WZB research group “Globalization, Work and Production” was obtained and feedback on question formulations was received from various sources.

In some instances, the questions include generic examples, such as “speech recognition software”, “translation programs” or “cobots”, aim to reduce the abstraction of the questions and thus simplify answering. However, brand names or specific applications were omitted to ensure longevity of the survey items and to avoid including information that might quickly become obsolete. In retrospect, this proved to be the right decision. During development, the company OpenAI published *ChatGPT*. Within a short time, *ChatGPT* became synonymous with generative artificial intelligence. Examples involving brand names could not have anticipated such a development and would have possibly led to measurement errors.

3.1. Pretest & Pilot

Cognitive pretests were conducted in September and October 2022. During the first round of pretests, it became clear that although the items were generally well understood, some respondents found them ambiguous. Therefore, the items were reworded based on these interim findings. A total of 15 respondents, all currently employed, aged 29–63, were interviewed by phone. Some were recruited via the researchers' private networks, and some via the LfBi's participants pool. After interviewing nine participants (eight with higher education and one with intermediate education), it was decided to focus the second round on five respondents with intermediate education and one with a high school diploma. Most respondents could clearly confirm whether or not a digital assistance system was used. However, some respondents were uncertain about what counted as such technology and sometimes incorrectly answered "yes" (false positives). Upon follow-up, these responses were often corrected.

During the pretest, we replaced "automatic [automatisch]" with "independent [selbstständig]". Emphasizing this aspect was relevant, as respondents had initially mentioned general computer programs rather than specific assistance systems. The stronger focus on independent task completion was supposed to highlight the novel, predictive or generative nature of these systems. Generic examples such as "speech recognition software," "translation programs," or "cobots" were added to reduce abstraction and facilitate responses. Between the two rounds of pretests, we observed an increase in plausible negative responses (true negatives) and an improvement in understanding. The examples in the second round proved helpful, although they were kept generic rather than specific¹.

Further minor adjustments were made to reduce respondent uncertainty to answering "never" on multiple items in a row. For example, the introduction was updated including a remark that the questions refer to newer technologies.

From October to December 2022, the Center for Empirical Social Research (ZeS) at Humboldt University Berlin was tasked with conducting a CATI survey to test the items on a larger scale. A total of 240 completed interviews were obtained through randomly dialed landline and mobile numbers. The targeted quota sample by age, employment sector, and education was partially achieved. All respondents were aged 25–64 and employed.

Based on the heuristic that one item takes ~15 seconds, the total survey duration was estimated at 135 seconds (8 items plus introduction). The pilot study exceeded this estimate at 152 seconds. Hence, additional revisions were made to the introduction, the interviewer instructions were refined, and the question texts were shortened. To further reduce overall interview duration, two items on the use of digital assistance systems for text and speech processing were merged. Finally, after being deployed in NEPS SC4/6 survey wave 16, the average unweighted duration for the "Digital Assistance Systems" section was 135 seconds.

3.2. Overview of final construct

The construct comprises seven items (and an introduction), which are formulated as frequency queries. The following table shows the individual items and scales.

¹ In one question variant with very specific examples using brand names, it was noted that this was rather confusing.

Table 2

List of item formulations and scale

Item	SUF variable	German	English
Intro		Eine neuere Form von digitalen Technologien sind digitale Assistenzsysteme. Das sind Computerprogramme oder Geräte, die selbstständig Aufgaben erledigen und dadurch Menschen bei der Arbeit unterstützen. Wir würden gerne mehr darüber erfahren, ob bei Ihrer Tätigkeit als <<...>> solche digitalen Assistenzsysteme zum Einsatz kommen.	A newer form of digital technologies are digital assistance systems. These are computer programs or devices that independently complete tasks and thereby support people at work. We would like to learn more about whether such digital assistance systems are used in your work as <<...>>.
Item stem		Wie häufig arbeiten Sie bei ihrer Tätigkeit mit...	In your job, how often do you work with...
Item 1	th60020	...Computerprogrammen oder Geräten, die Text oder Sprache selbstständig erstellen, erkennen oder übersetzen? Beispiele dafür sind Schrifterkennung, Spracherkennungssoftware, Übersetzungsprogramme sowie Textgeneratoren.	...computer programs or devices that independently create, recognize or translate text or speech? Examples include text and speech recognition, translation programs as well as text generators.
Item 2	th60021	...Computerprogrammen oder Geräten, die Bilder oder Videos selbstständig erstellen, erkennen oder bearbeiten?	...computer programs or devices that independently create, recognize or edit images or videos?
Item 3	th60022	...Computerprogrammen oder Geräten, die selbstständig Fragen zu Fachwissen beantworten oder Informationen bereitstellen? Beispiele sind unter anderem Chatbots oder Dashboards.	...computer programs or devices that independently answer questions about specialized knowledge or provide information? Examples include chatbots or dashboards.
Item 4	th60023	...Computerprogrammen oder Geräten, die selbstständig Daten aufbereiten oder Diagnosen stellen?	...computer programs or devices that automatically prepare data or make diagnoses?
Item 5	th60024	Wie häufig bekommen Sie bei Ihrer Tätigkeit Arbeitsanweisungen, die nicht von Personen, sondern automatisch von Geräten, Computerprogrammen oder Apps erstellt werden?	How often do you receive work instructions in your job that are not created by people, but automatically by devices, computer programs or apps?

Item 6	th60025	...digitalen Geräten, die Sie am Körper tragen - auch Wearables genannt - zum Beispiel Datenbrillen, Smartwatches oder andere intelligenten Kleidungsstücke?	...digital devices that you wear on your body - also called wearables - for example smart glasses, smart watches or other smart clothing?
Item 7	th60026	...digitalen Geräten, die selbstständig körperlich-anstrengende Aufgaben übernehmen, wie Roboterarme oder Cobots?	...digital devices that independently take over physically strenuous tasks, such as robot arms or cobots?
Interviewer instructions		[Int.: Skala vorlesen] (für Item 1 und 2) [Int.: Skala nur bei Bedarf vorlesen] (für Items 3-7)	[Int.: Read out scale] (for Items 1 and 2) [Int.: Read out scale only if needed] (for Items 3-7)
Scale		1. Nie 2. Selten 3. Manchmal 4. Oft 5. Sehr oft • Weiß nicht / Keine Angabe	1. Never 2. Rarely 3. Sometimes 4. Often 5. Very often • Don't know / No Response

3.3. Cohort, target group, survey rhythm

The items are intended for currently employed respondents of NEPS Cohorts SC4 and SC6. Their current occupation is inserted in the introduction to reinforce the anchoring of the answers in their current job. To answer questions about changes in the use of digital assistance systems, a longitudinal measurement is necessary. Ideally, the construct will be used in the same survey rhythm as the constructs “job tasks” and “digitalization of the world of work” which are deployed every three years, due to its thematic proximity. The first deployment occurred in SC4 and SC6 wave 16 (September 2023 - April 2024), and further use is planned from 2026/27.

4. Descriptive statistics

Table 3 shows the distribution of responses to digital assistance systems items in NEPS SC4/6 (NEPS Network, 2025a, 2025b). Due to employment-based filtering, N = 1,911 respondents who were not working at the time of the survey did not receive these items. Overall, the response was refused once (Instructions) and the answer “don’t know” was given on rare occasions. We interpret the low frequency of many missing values due to “Don’t know” answers and the relatively large share of “Never” answers as evidence of items’ good specificity.

Table 3

Distribution of digital assistance systems. NEPS SC4/6 SUF 16.0.0.

	Text/ Language	Images/ Videos	Knowledge	Data/ Diagnoses	Instructions	Wearables	Cobots
0 Never	2,606 (36.3%)	4,061 (56.6%)	3,514 (49.0%)	3,375 (47.1%)	4,164 (58.1%)	4,817 (67.2%)	5,001 (69.7%)
1 Rarely	1,331 (18.6%)	840 (11.7%)	1,018 (14.2%)	1,038 (14.5%)	716 (10.0%)	237 (3.3%)	129 (1.8%)
2 Sometimes	787 (11.0%)	239 (3.3%)	437 (6.1%)	433 (6.0%)	248 (3.5%)	79 (1.1%)	50 (0.7%)
3 Often	350 (4.9%)	80 (1.1%)	206 (2.9%)	300 (4.2%)	89 (1.2%)	62 (0.9%)	48 (0.7%)
4 Very often	183 (2.6%)	37 (0.5%)	81 (1.1%)	107 (1.5%)	39 (0.5%)	63 (0.9%)	31 (0.4%)
N (valid)	5,257 (73.3%)	5,257 (73.3%)	5,256 (73.3%)	5,253 (73.3%)	5,256 (73.3%)	5,258 (73.3%)	5,259 (73.3%)
Missing							
Don’t know	3 (0.04%)	3 (0.04%)	4 (0.06%)	7 (0.10%)	3 (0.04%)	2 (0.03%)	1 (0.01%)
Refused	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	1 (0.01%)	0 (0.00%)	0 (0.00%)
By design	1,911 (26.7%)	1,911 (26.7%)	1,911 (26.7%)	1,911 (26.7%)	1,911 (26.7%)	1,911 (26.7%)	1,911 (26.7%)
Total	7,171 (100%)	7,171 (100%)	7,171 (100%)	7,171 (100%)	7,171 (100%)	7,171 (100%)	7,171 (100%)
Mean	0.89	0.32	0.54	0.62	0.31	0.16	0.09
SD	1.10	0.70	0.91	0.99	0.71	0.61	0.48
Skewness	1.14	2.59	1.83	1.67	2.69	4.59	5.96

Figure 1 shows that text/speech systems are the only type of digital assistance system used by a majority of respondents, though only by a narrow margin. Other digital assistance systems are used less. Cobots and Wearables are least used, followed by receiving instructions. Still, between one-fifth and one-third of respondents reported using digital assistance systems for image/videos, knowledge, or data/diagnoses at least occasionally.

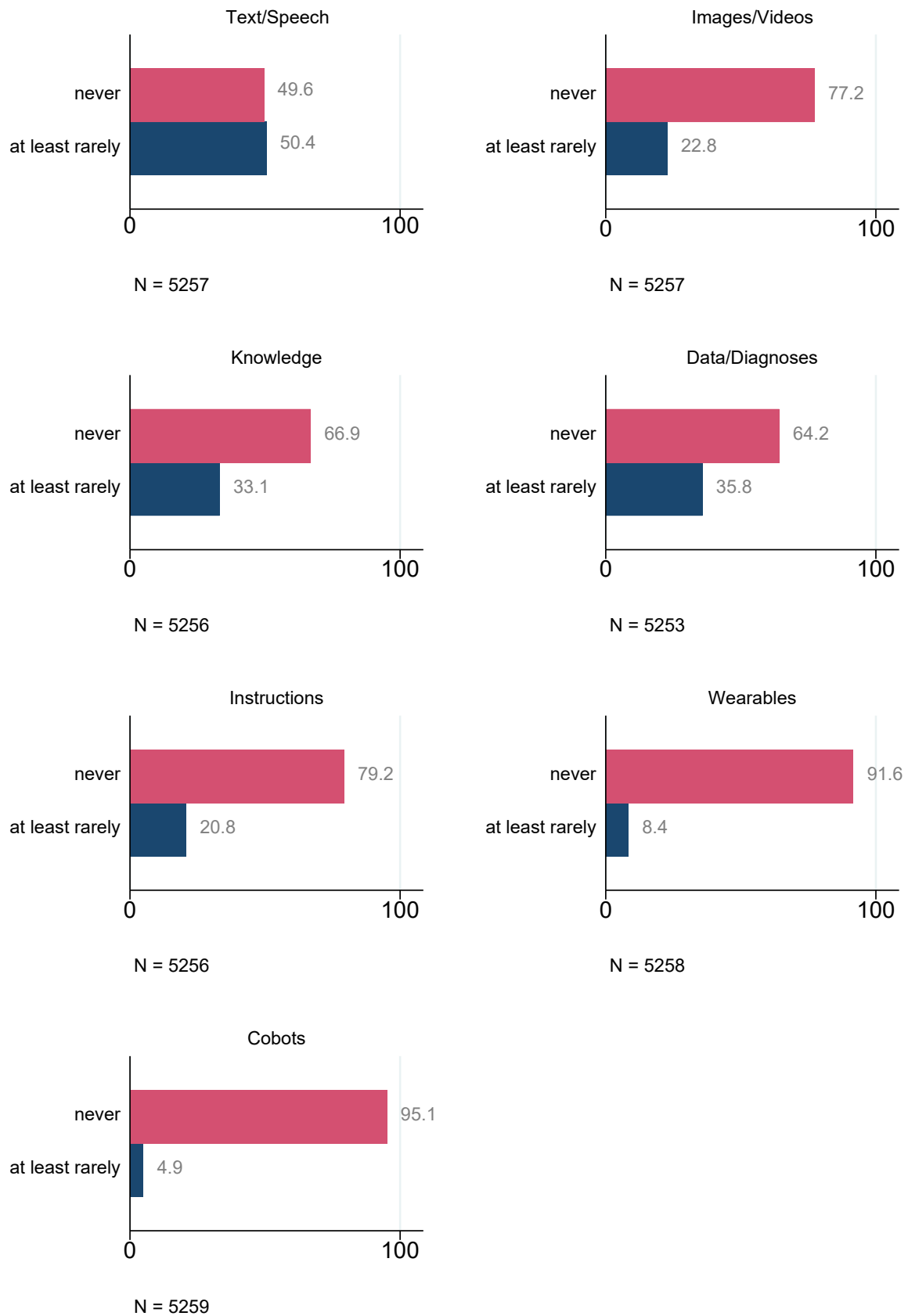


Figure 1. Usage of digital assistance systems. NEPS SC4/6 SUF 16.0.0

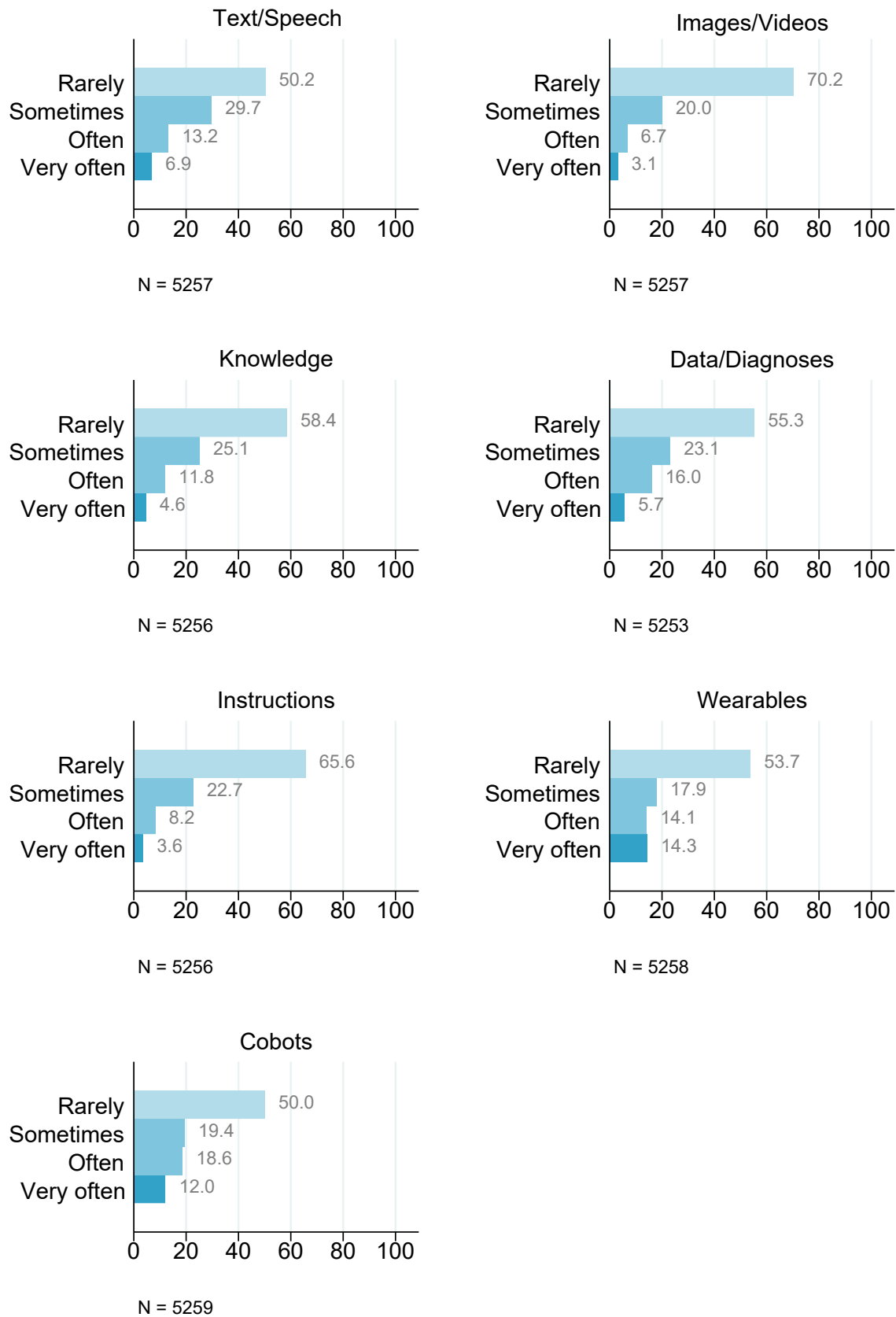


Figure 2. Distribution of usage frequency of digital assistance systems in percent (“Never” category omitted). NEPS SC4/6 SUF 16.0.0

Figure 2 provides a more detailed look at usage intensity among those who use each type of digital assistance system at least rarely. After omitting “Never”, “Rarely” is the most common response, confirming that the 2023/24 NEPS wave captures the early stages of a broader development. Most digital assistance systems have not yet become part of respondents’ regular professional routines. Rather, many workers appear to have tried or experimented with these tools without fully integrating them into their daily workflows. Notably, despite their low overall adoption rate, cobots and wearable systems appear more integrated into the routines of workers who do use them, as reflected in the relatively higher share of “Often” and “Very often” responses.

4.1. Correlations between items

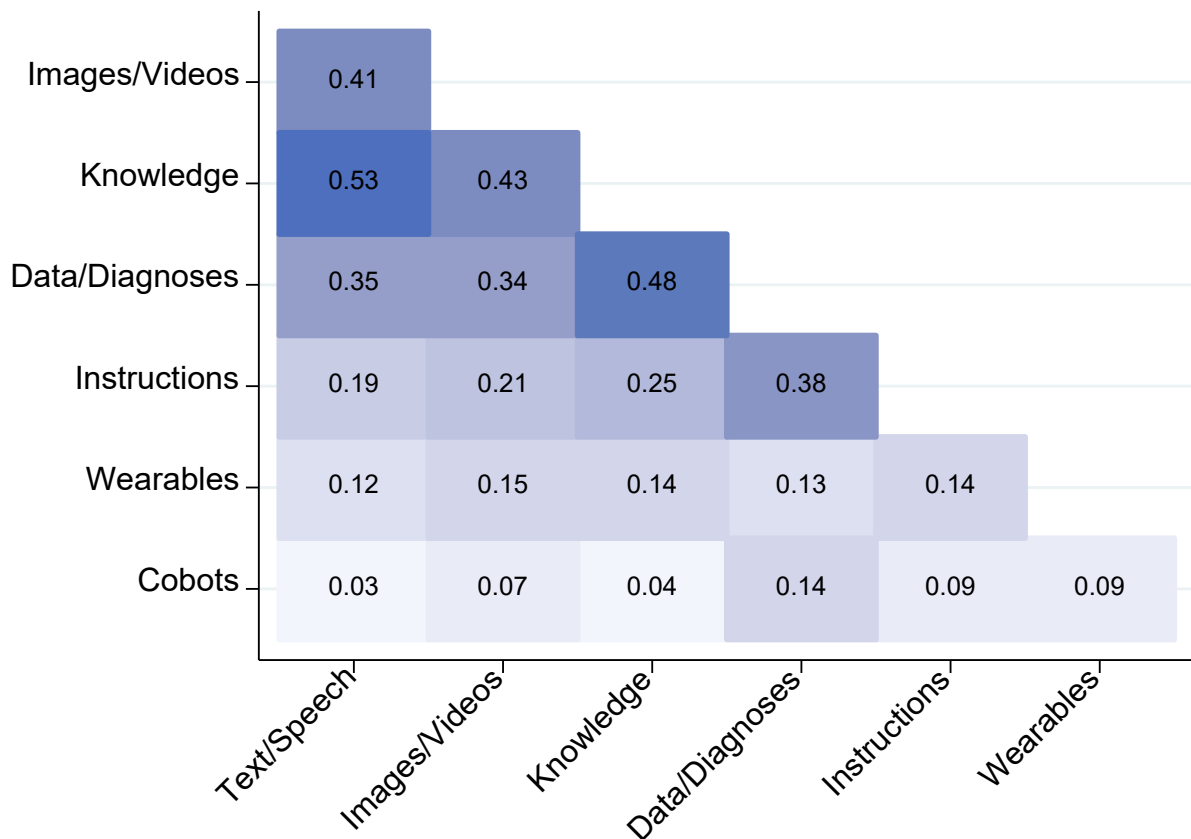


Figure 3. Pearson correlations between digital assistance systems. NEPS SC4/6 SUF 16.0.0

Figure 3 shows that some of the systems appear to be used together more frequently than others. This is particularly true of systems that process text, speech, and images and provide specialized knowledge. This is to be expected, as all these technologies can be used for office jobs, and many such capabilities are achievable using multi-modal LLM-based chatbots. Systems that provide data and diagnoses are also often used by the same people. Here, there is also a notable correlation with systems that provide instructions. Wearables and cobots, on the other hand, mostly correlate only weakly with the other systems. This suggests that these systems are used in different work environments or that they are generally used less frequently. These findings indicate that our items measure different forms of workplace digitalization.

4.2. Correlations between items and job tasks

As previously elaborated, the development of the survey items to measure digital assistance systems was firmly grounded in the task-based approach (Autor et al. 2003; Spitz-Oener 2006; Matthes et al., 2014). We formulated the items with existing job task classifications in mind, and we expected the items to correlate with job task measurements in the NEPS.

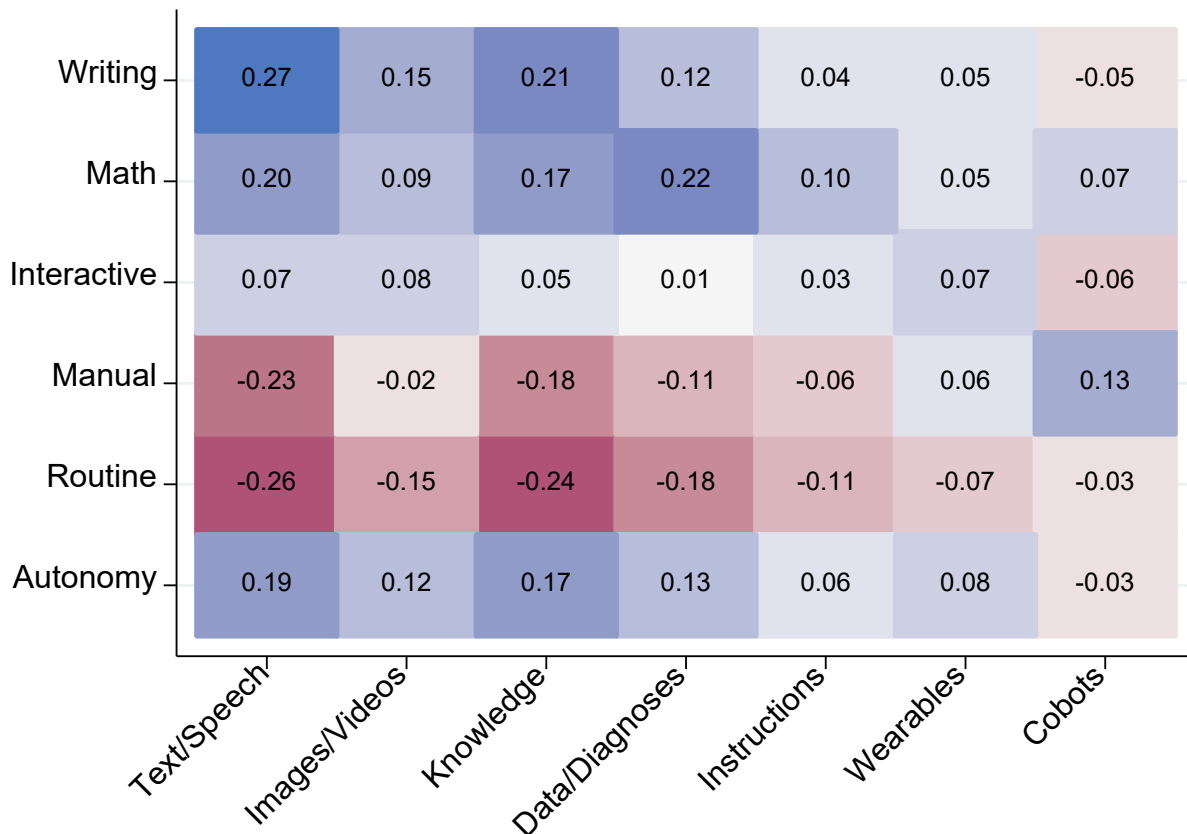


Figure 4. Pearson correlations between digital assistance systems and job tasks. NEPS SC4/6 SUF 16.0.0

Figure 4 shows that performed job tasks do correlate with the use of digital assistance systems in the expected patterns. Respondents who perform analytical tasks more frequently in their job, such as writing texts and using math, also report the use of systems that support them in these tasks more frequently (Text/Speech, Specialized Knowledge, Data/Diagnoses). Respondents who perform more manual and routine tasks tend to use these systems less. This supports our expectation that these systems are primarily used in non-routine, cognitively oriented jobs. On the other end of the cognitive-manual spectrum, and in line with our expectations, there is a small positive correlation of manual tasks with cobots. However, contrary to our expectations, routine tasks correlate negatively with receiving digital work instructions and using wearables. This could imply that routine contents of jobs where these technologies are applied have already been replaced by such systems. Alternatively, it may be that such systems are only applied in less structured work environments to aid workers who have to perform several different tasks. The repeated measurement of job tasks and assistance systems in the future will shed more light on these mechanisms.

4.3. Correlations between items and software use

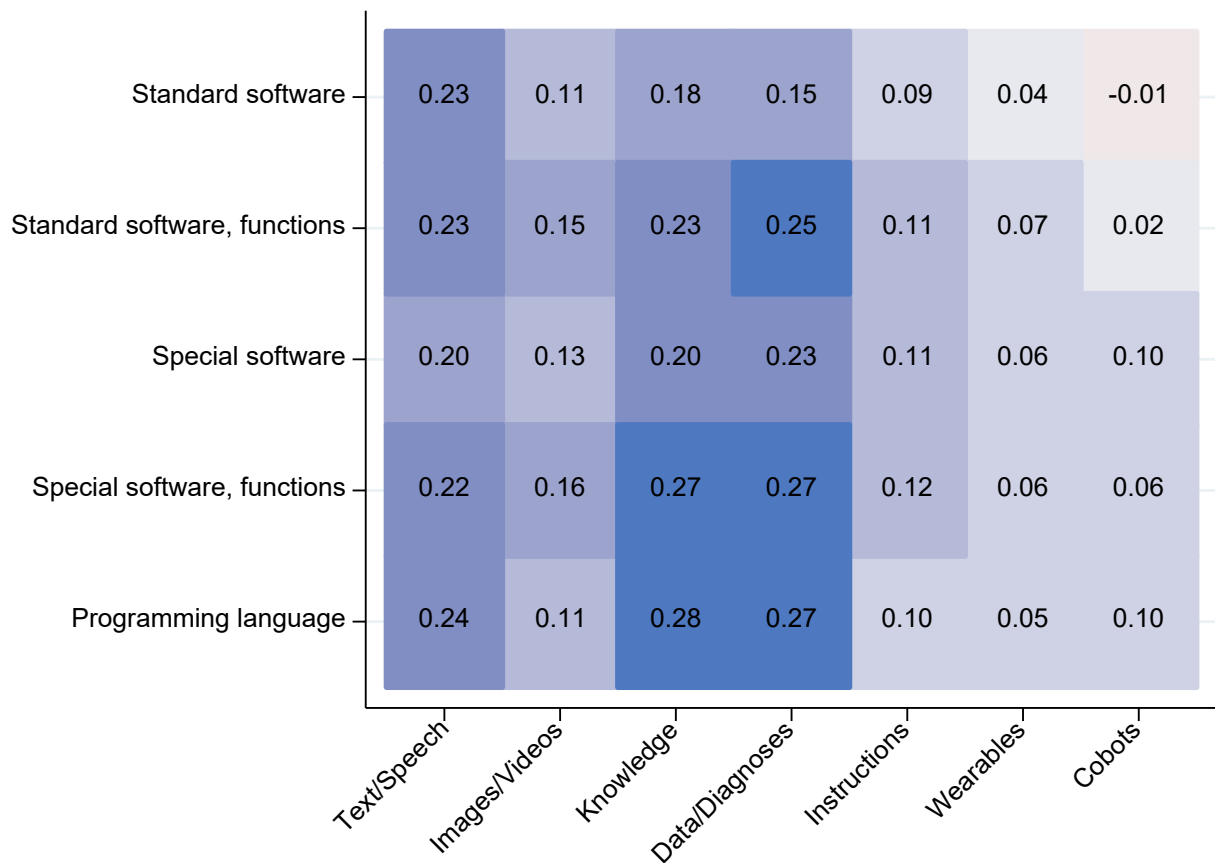


Figure 5. Pearson correlations between digital assistance systems and software use. NEPS SC4/6 SUF 16.0.0

Figure 5 shows the associations of different levels of software use (sorted by sophistication) and the use of digital assistance systems. Generally, most types of software use correlate slightly positively with the use of digital assistance systems. We observe an increasing association for Knowledge and Data/Diagnoses systems as software use becomes more advanced. This gradient is consistent with the task-based framework and a complementary function of these tools: workers engaged in sophisticated analytical work are also more likely to use specialized software and programming languages and more receptive to digital assistance systems that complement cognitive tasks such as information retrieval and data preparation. In contrast, the associations for Text/Speech systems are relatively flat across software use levels, suggesting a broader appeal regardless of technical proficiency. Instructions, Wearables and Cobots show consistently weak associations with software use, which aligns with the expectation that these hardware-based systems operate in distinct occupational contexts such as manufacturing or logistics, where software sophistication is less predictive of adoption.

4.4. Correlations between items and occupation-based indicators

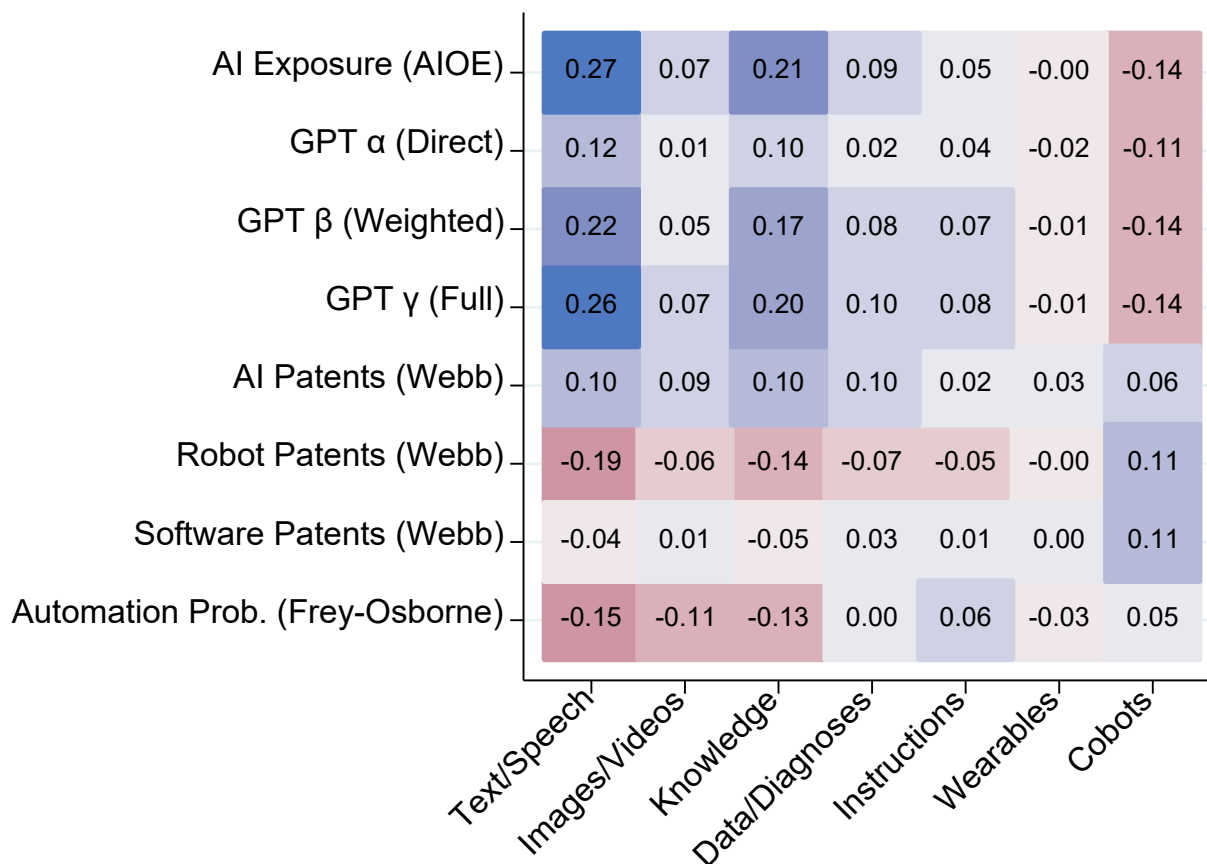


Figure 6. Pearson correlations between digital assistance systems and occupation-based indicators of workplace automation. NEPS SC4/6 SUF 16.0.0

Figure 6 shows the correlations between occupation-based indicators merged via the respondents' indicated current occupation of AI and automation exposure and the individual-level use of digital assistance systems. The AI Occupational Exposure index (Felten et al., 2021), as well as the GPT exposure indicators (Eloundou et al., 2024), correlate positively with the use of text/speech and knowledge systems. These positive correlations provide validation for our measures: occupations that experts classify as highly exposed to AI capabilities are indeed the ones where workers report using AI-related digital assistance systems more frequently. The AI and software patent indicators (Webb, 2019) do not show strong correlations with our items. Robot patent exposure, however, correlates negatively with most digital assistance systems but positively with cobots. Similarly, automation probabilities based on Frey and Osborne (2017) correlate negatively with the use of text/speech, knowledge, and data/diagnosis systems. We interpret these patterns as follows: The Frey-Osborne and robot patent indicators capture exposure to more traditional, mechanical forms of automation that predominantly affect manual and routine tasks. In contrast, our text/speech and knowledge items capture newer forms of cognitive automation. The small positive correlation between robot patents and cobot use confirms that these indicators measure exposure to physical automation technologies. Notably, image/video systems, data/diagnosis tools, work instructions, and wearables do not systematically correlate with any of these occupation-level

indicators. This suggests that these digital assistance systems represent distinct forms of workplace technology adoption not fully captured by existing occupation-based exposure measures. Overall, our individual-level items complement and extend what occupation-based indicators can measure by capturing heterogeneity in technology use within occupations.

4.5. Usage by age

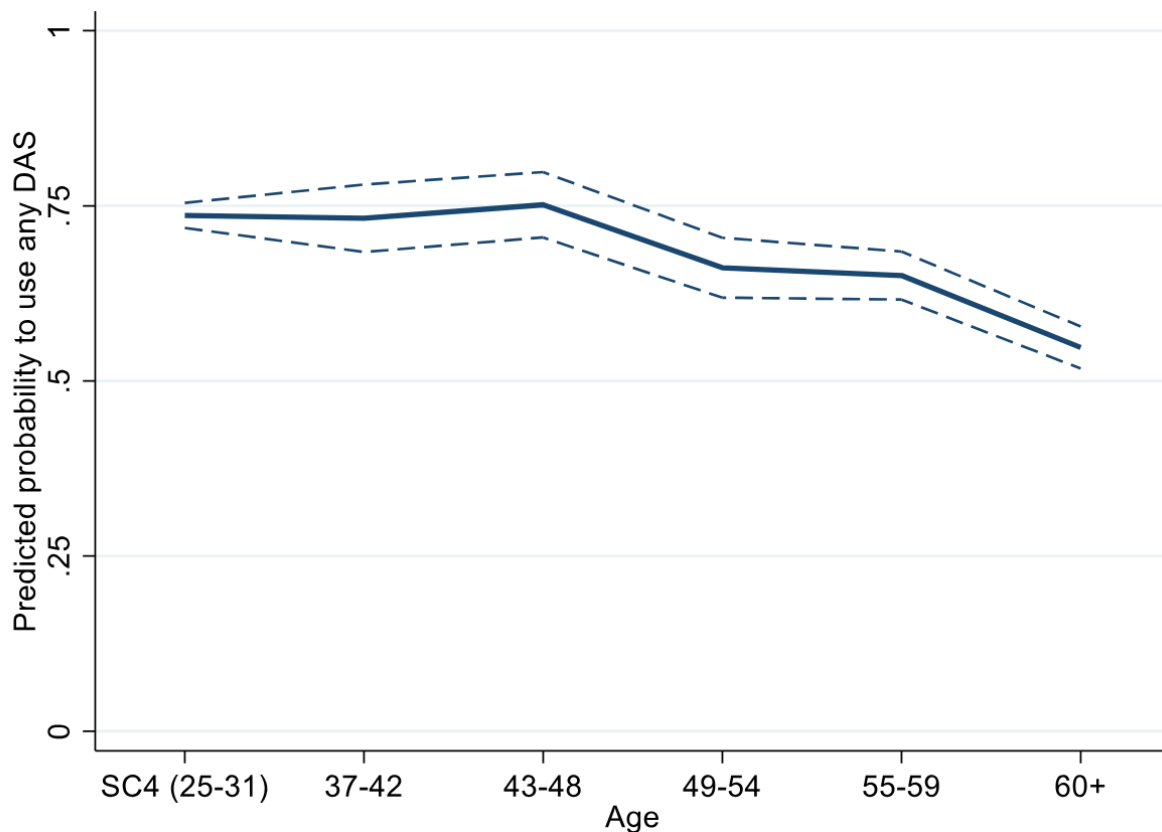


Figure 7. Predicted probability of use of any digital assistance system by age, based on logistic regression (see Appendix 2). NEPS SC4/6 SUF 16.0.0

Figure 7 displays the probability of using at least one digital assistance system by age. A lower usage rate can be seen among older employees, mirroring previous findings in the literature on adoption of new technology and age (e.g. Fasbender et al., 2023).

4.6. Usage by level of education

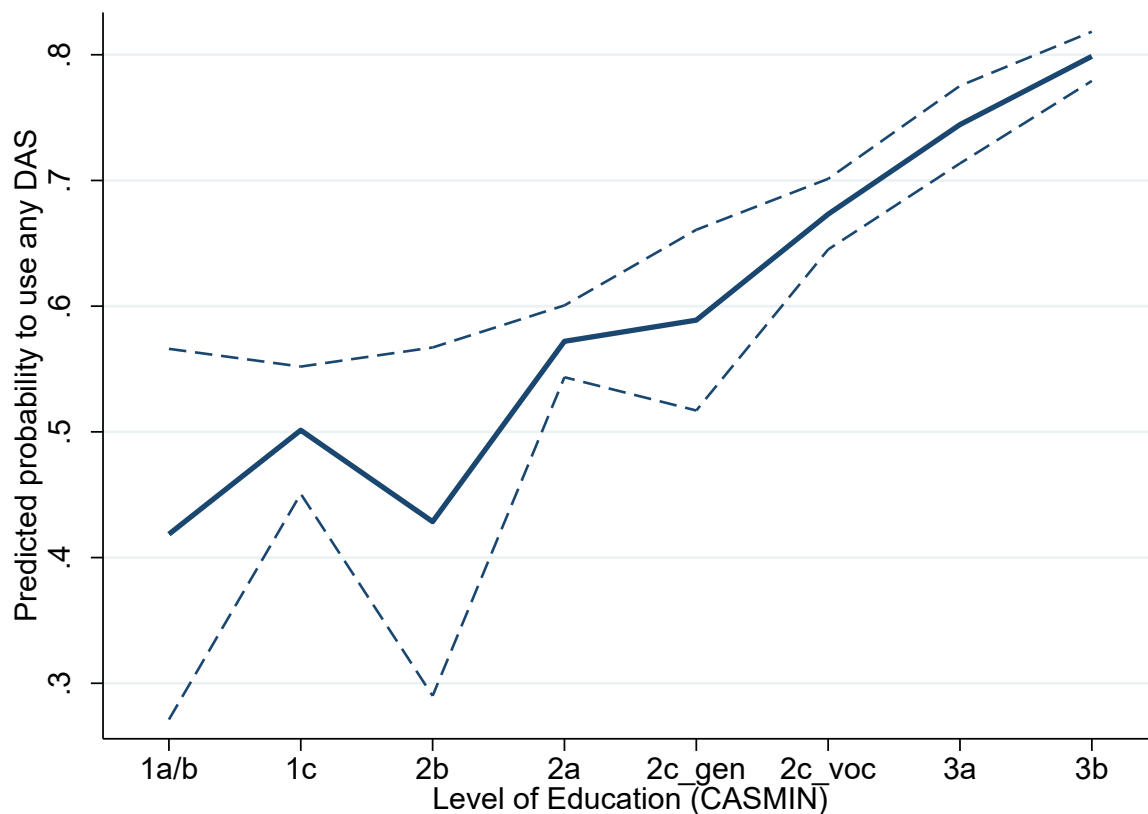


Figure 8. Predicted probability of use of any digital assistance system by level of education, based on logistic regression (see Appendix 3). NEPS SC4/6 SUF 16.0.0

Figure 8 shows that the use of digital assistance systems varies by respondents' CASMIN level of education (see Appendix 1 for a description of the levels). We combine levels 1a with 1b due to the limited number of cases in level 1a in the NEPS data. Generally, respondents with higher levels of education, from lower (level 1), to intermediate (level 2) to university-level education (level 3), are more likely to use digital assistance systems. However, examining this education effect separately for the various digital assistance systems and comparing it to the use of standard and specialized software (Figure 9) reveals that the education effect varies in strength and direction depending on the assistance system considered. This trend aligns with our expectation that some of the items also capture usage in activities that are more likely to be used by employed individuals with lower education levels.

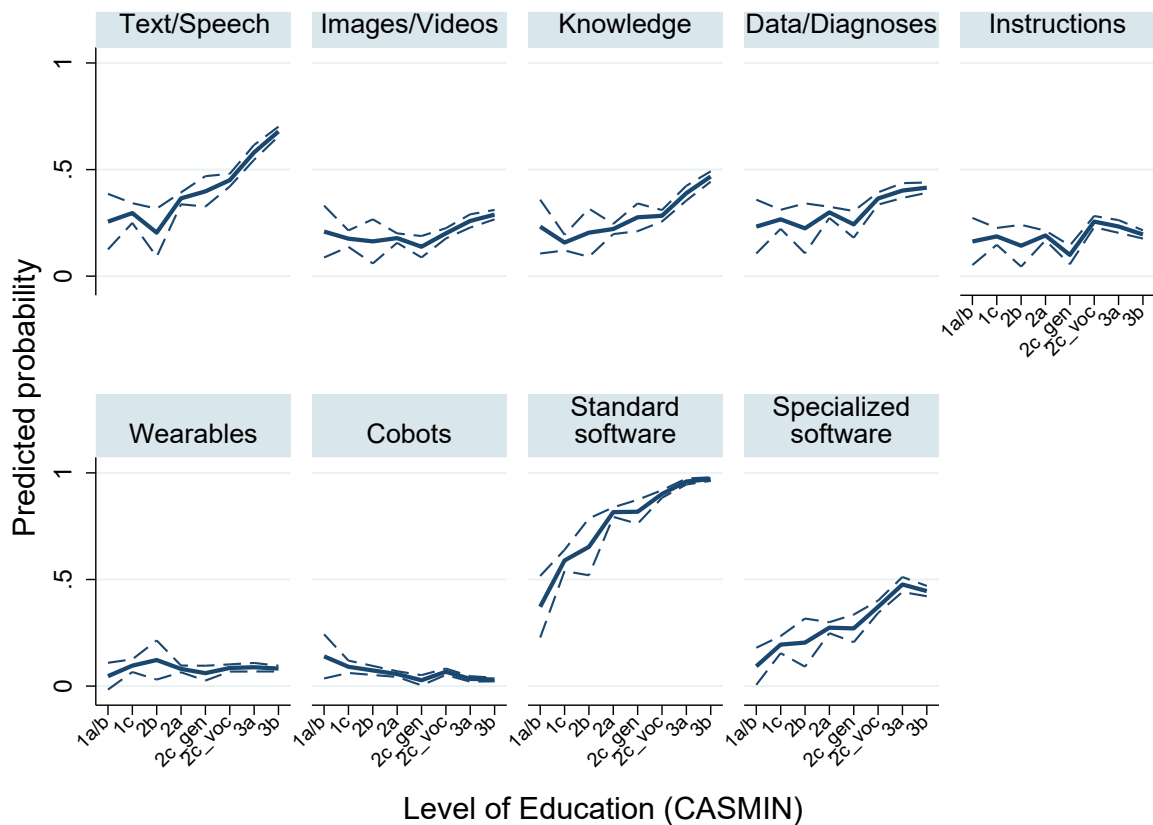


Figure 9. Probability of usage of digital assistance systems and software by level of education, based on logistic regressions (see Appendix 4). NEPS SC4/6 SUF 16.0.0

Figure 9 shows the probability of using digital assistance systems by education level (CASMIN) and offers a more detailed view than Figure 8. The positive correlation between education and overall usage (Figure 8) seems to be mainly driven by text/speech and knowledge systems, particularly among university-educated users (CASMIN 3a, 3b). We see slightly weaker correlations for image/video generation and data/diagnosis tools, and instruction-based systems. For wearables and cobots, however, the trend reverses slightly. Comparing the different digital assistance systems to each other and to the use of standard or specialized software reveals considerable heterogeneities. While text and speech assistance systems have a clear and steep positive correlation with education, other systems correlate less strongly with education. Partly, this is due to overall lower adoption, such as for the case of wearables. Partly, like in the case of image/videos and for data/diagnoses, the correlation with education is flatter than for text/speech. Standard software is the most widely adopted and serves as a benchmark to compare digital assistance systems to. Among intermediate and higher educated respondents, the correlation is rather flat. For specialized software, the pattern is again steeper towards the higher end of the education distribution.

4.7. Perceived external control, digitalization, automation

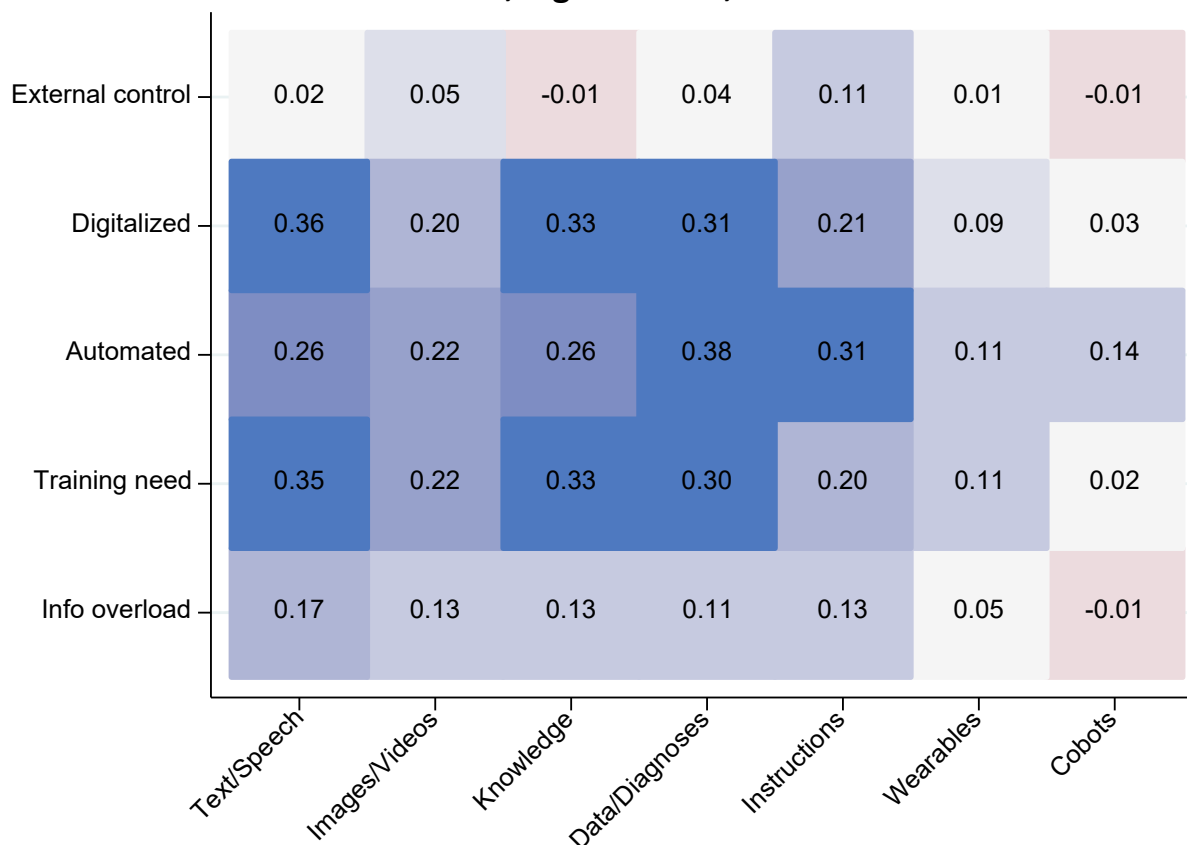


Figure 10. Pearson correlations between digital assistance systems and workplace digitalization. NEPS SC4/6.

Figure 10 shows the bivariate correlations between using digital assistance systems and indicators of workplace digitalization: perceived external control, degree of digitalization, degree of automation, training need, and information overload. Perceived external control does not systematically correlate with most digital assistance system usage, except for a small positive correlation with receiving instructions via digital assistance systems. The reported degree of workplace digitalization has moderate positive correlations with the use of digital assistance systems, most notably the use of Text/Speech systems, as well as Knowledge and Data/Diagnoses. The reported degree of workplace automation has moderate positive correlations with the use of digital assistance systems, most notably with Data/Diagnoses and Instructions. Compared to the other aspects of digitalization, workplace automation shows a positive correlation with the use of cobots. Training need correlates positively with the more cognitive oriented systems. This pattern suggests that workers who use such systems perceive greater demands for own skill development, potentially reflecting an “upskilling” dynamic. Information overload shows modest positive correlations across most systems, particularly Text/Speech, though the associations are weaker than for training need. This may indicate that while these tools generate some cognitive burden, the effect is limited.

5. Conclusion

The items presented here will fill a significant knowledge gap in current discussions about the role of digital technologies and artificial intelligence in the workplace. NEPS data furthermore make it possible to link changes in the workplace to the expected penetration of AI-supported digital assistance systems with detailed employment and education biographies. Thus, the data can be used to examine the much-discussed relationship between digitalization, workplace competency requirements, and education. Overall, the presented items complement the existing NEPS items on workplace digitalization and job tasks.

The items appear to function well as measures of digital assistance system usage in the workplace. Several indicators support this assessment. First, the low proportion of “Don’t know” responses suggests that respondents found the items comprehensible and were able to provide meaningful answers. Second, the distribution of responses across the frequency scale indicates appropriate item sensitivity, with sufficient variation to distinguish between different levels of technology adoption. Third, the correlations between items follow theoretically expected patterns: cognitive-oriented systems cluster together, while manual and hardware-based systems form a distinct group. Fourth, the items show the expected correlations with occupation-based indicators of technology exposures.

The descriptive findings also offer substantive insights into the current state of digital assistance system adoption. The relatively high proportion of “Never” responses across most items suggests that, at the time of data collection, despite considerable public attention to artificial intelligence and automation technologies, actual workplace adoption remains limited for many employees. This finding is particularly notable for wearables and collaborative robots, which are still used by only a small minority of workers. At the same time, the fact that roughly half of respondents have used text and speech systems at least occasionally indicates that certain forms of digital assistance have already achieved meaningful penetration in the workforce. The longitudinal design of NEPS will enable the tracking of these adoption patterns as technologies mature.

While the items were not developed with a latent structure in mind, and we do not recommend treating them as such, the observed pattern of correlations suggests that the items can be grouped by cognitively oriented and manual or hardware-based applications. We additionally explored their empirical structure using factor analysis. The results suggest substantively meaningful groupings into a cognitive and a manual factor (see Appendix 6). Treating items 1 to 4 as one scale yields a Cronbach’s alpha of .73. Nevertheless, the items were designed to capture related but distinct forms of digital assistance system use. The appropriate level of aggregation therefore depends on the research question, but in most applications we recommend analyzing the items separately.

The integration of these measures with the rich biographical and competence data available in NEPS positions the study to make important contributions to our understanding of technological change and its implications for workers, employers, and policy makers.

Looking ahead, the repeated administration of these items will enable researchers to examine questions that cannot be addressed with cross-sectional data alone. Future measurements will make it possible to investigate whether digital assistance systems lead to changes in skill

requirements and training needs, how adoption trajectories differ across occupational groups, and whether early adopters experience different outcomes than later adopters. While the task-based and technology-neutral wording of the items was deliberately chosen to remain applicable under conditions of rapid technological change, qualitative follow-up studies could assess how the items capture recently available AI-based tools.

Bibliography

- Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of Economic Literature*, 40(1), 7–72.
- Autor, D. H., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, 118(4), 1279–1333.
<https://doi.org/10.1162/003355303322552801>
- Autor, D. H., & Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, 103(5), 1553–1597.
<https://doi.org/10.1257/aer.103.5.1553>
- Blossfeld, H.-P. & Roßbach, H.-G. (Eds.). (2019). Education as a lifelong process: The German National Educational Panel Study (NEPS). *Edition ZfE* (2nd ed.). Springer VS.
- Braverman, H. ([1974] 1998). *Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century*. Monthly Review Press.
- Brynjolfsson, E., & McAfee, A. (2012). *Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*. Digital Frontier Press.
- Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2024). GPTs are GPTs: Labor market impact potential of LLMs. *Science*, 384, 1306–1308. <https://doi.org/10.1126/science.adj0998>
- Fedorets, A., Kirchner, S., Adriaans, J., & Giering, O. (2022). Data on Digital Transformation in the German Socio-Economic Panel: *Jahrbücher Für Nationalökonomie Und Statistik*, 242(5–6), 691–705. <https://doi.org/10.1515/jbnst-2021-0056>
- Fasbender, U., Gerpott, F. H., & Rinker, L. (2023). Getting Ready for the Future, Is It Worth It? A Dual Pathway Model of Age and Technology Acceptance at Work. *Work, Aging and Retirement*, 9(4), 358–375. <https://doi.org/10.1093/workar/waac035>
- Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12), 2195–2217. <https://doi.org/10.1002/smj.3286>
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280.
<https://doi.org/10.1016/j.techfore.2016.08.019>

- Friedrich, T. S., Laible, M.-C., Müller, C., Pollak, R., Schongen, S., Schulz, B., & Vicari, B. (2022). Digitalisierung der Arbeitswelt – ein Messinstrument der NEPS-Erwachsenenbefragungen (1.0) [NEPS Survey Papers]. LIfBi. https://www.lifbi.de/Portals/2/NEPS%20Survey%20Papers/NEPS-Survey-Paper_XCII.pdf
- Gensler, E., & Abendroth, A.-K. (2021). Verstärkt algorithmische Arbeitssteuerung Ungleichheiten in Arbeitsautonomie? *SozW Soziale Welt*, 72(4), 514–550. <https://doi.org/10.5771/0038-6073-2021-4-514>
- Giering, O., Fedorets, A., Adriaans, J., & Kirchner, S. (2021). Künstliche Intelligenz in Deutschland: Erwerbstätige wissen oft nicht, dass sie mit KI-basierten Systemen arbeiten. *DIW-Wochenbericht* 48/2021. https://doi.org/10.18723/diw_wb:2021-48-1
- Giering, O., & Kirchner, S. (2021). Künstliche Intelligenz am Arbeitsplatz. *SozW Soziale Welt*, 72(4), 551–588. <https://doi.org/10.5771/0038-6073-2021-4-551>
- Hecker, D., Döbel, I., Petersen, U., Rauschert, A., Schmitz, V., & Voss, A. (2017). Zukunftsmarkt Künstliche Intelligenz – Potenziale und Anwendungen. Fraunhofer-Allianz Big Data. https://www.iais.fraunhofer.de/content/dam/bigdata/de/documents/Publikationen/KI-Potenzialanalyse_2017.pdf
- Kelly, P., Lawlor, J., & Mulvey, M. (2019). Self-service Technologies in the Travel, Tourism, and Hospitality Sectors: Principles and Practice, In Ivanov, S. & Webster, C. (eds.) *Robots, Artificial Intelligence, and Service Automation in Travel, Tourism and Hospitality*. Emerald Publishing Limited: Bingley, pp. 57–78. <https://doi.org/10.1108/978-1-78756-687-320191003>
- Krzywdzinski, M., Pfeiffer, S., Evers, M., & Gerber, C. (2022). Measuring work and workers: Wearables and digital assistance systems in manufacturing and logistics (Discussion Papers, Research Group Globalization, Work, and Production SP III 2022-301). WZB. <https://ideas.repec.org//p/zbw/wzbgwp/spiii2022301.html>
- Lane, M., & Saint-Martin, A. (2021). The impact of Artificial Intelligence on the labour market: What do we know so far? *OECD Social, Employment and Migration Working Papers* 256. <https://dx.doi.org/10.1787/7c895724-en>
- Lukanova, G., & Ilieva, G. (2019). Robots, artificial intelligence, and service automation in hotels. In Ivanov, S. & Webster, C. (eds.) *Robots, Artificial Intelligence, and Service Automation in Travel, Tourism and Hospitality*. Emerald Publishing Limited: Bingley, pp. 157–183. <https://doi.org/10.1108/978-1-78756-687-320191009>

- Martinaitis, Ž., Christenko, A., & Antanavičius, J. (2021). Upskilling, Deskilling or Polarisation? Evidence on Change in Skills in Europe. *Work, Employment and Society*, 35(3), 451–469.
<https://doi.org/10.1177/0950017020937934>
- Matthes, Britta, Bernhard Christoph, Florian Janik & Michael Ruland (2014): Collecting information on job tasks - an instrument to measure tasks required at the workplace in a multi-topic survey. In: *Journal for labour market research*, Jg. 47, H. 4,S. 273-297. DOI:10.1007/s12651-014-0155-4
- NEPS Network. (2025a). National Educational Panel Study, Scientific Use File of Starting Cohort Grade 9. Leibniz Institute for Educational Trajectories (LifBi), Bamberg.
<https://doi.org/10.5157/NEPS:SC4:16.0.0>
- NEPS Network. (2025b). National Educational Panel Study, Scientific Use File of Starting Cohort Adults. Leibniz Institute for Educational Trajectories (LifBi), Bamberg.
<https://doi.org/10.5157/NEPS:SC6:16.0.0>
- Oesch, D., & Piccitto, G. (2019). The Polarization Myth: Occupational Upgrading in Germany, Spain, Sweden, and the UK, 1992–2015. *Work and Occupations*, 46(4), 441–469.
<https://doi.org/10.1177/0730888419860880>
- Reimann, M., Abendroth, A.-K., & Diewald, M. (2020). How digitalized is work in large German workplaces, and how is digitalized work perceived by workers? A new employer-employee survey instrument (IAB-Forschungsbericht 8/2020). Institut für Arbeitsmarkt- und Berufsforschung.
- Reimann, M., & Tisch, A. (Hrsg.). (2021). *Arbeits und Beschäftigungsqualität in digitalisierten Arbeitswelten*. Sonderheft Soziale Welt 4/2021. Baden-Baden: Nomos.
- Spitz-Oener, A. (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>
- SOEP-IS Group, 2021. SOEP-IS 2019 – Fragebogen für die SOEP-Innovations-Stichprobe. SOEP Survey Papers 953: Series A – Survey Instruments (Erhebungsinstrumente). Berlin: DIW Berlin/SOEP
- Wang, L., Liu, Z., Liu, A., & Tao, F. (2021). Artificial intelligence in product lifecycle management. *The International Journal of Advanced Manufacturing Technology* 114, 771–796.
<https://doi.org/10.1007/s00170-021-06882-1>
- Webb, M. (2019). The Impact of Artificial Intelligence on the Labor Market. *SSRN Electronic Journal*.
<https://doi.org/10.2139/ssrn.3482150>

Appendix

Appendix 1: Overview of CASMIN scale.

Level	CASMIN Code	German Education Level	Description
Primary	1a	Ohne Abschluss, berufliches Praktikum	Inadequately completed general elementary education
	1b	Haupt-/Volksschulabschluss	General elementary education
	1c	Haupt-/Volksschulabschluss mit abgeschlossener Lehr-/Anlernausbildung oder Meister-/Technikerausbildung	General elementary education with basic vocational training
Intermediate	2b	Realschulabschluss (Mittlere Reife)	Intermediate general qualification
	2a	Realschulabschluss (Mittlere Reife) mit abgeschlossener Lehr-/Anlernausbildung oder Meister-/Technikerausbildung	Intermediate qualification with vocational training
	2c_gen	Fachhochschulreife, Hochschulreife (Abitur)	General maturity certificate
	2c_voc	Fachhochschulreife, Hochschulreife (Abitur) mit abgeschlossener Lehr-/Anlernausbildung oder Meister-/Technikerausbildung	Vocational maturity certificate or combined qualification
Higher	3a	Fachhochschule, Ingenieurschule	Lower tertiary education
	3b	Hochschule	Higher tertiary education

Appendix 2: Logistic regression model for any DAS usage on age

	b/se
Age	
SC4 (25-31)	0.000 (.)
37-42	-0.021 (0.134)
43-48	0.079 (0.136)
49-54	-0.356*** (0.108)
55-59	-0.406*** (0.090)
60+	-0.836*** (0.078)
Constant	1.027*** (0.047)
N	5259

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ **Appendix 3:** Logistic regression model for any DAS usage on education

	b/se
CASMIN	
1a/b	0.000 (.)
1c	0.334 (0.326)
2b	0.041 (0.423)
2a	0.613 (0.315)
2c_gen	0.678* (0.344)
2c_voc	1.057*** (0.316)
3a	1.391*** (0.320)
3b	1.702*** (0.315)
Constant	-0.329 (0.309)
N	5257

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix 4: Logistic regression models for individual DAS items by education

	(1) Text b/se	(2) Images b/se	(3) Knowledge b/se	(4) Data b/se	(5) Instructions b/se	(6) Wearables b/se	(7) Cobots b/se
CASMIN							
1a/b	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
1c	0.201 (0.367)	-0.215 (0.399)	-0.481 (0.388)	0.182 (0.379)	0.201 (0.367)	-0.215 (0.399)	-0.481 (0.388)
2b	-0.293 (0.498)	-0.305 (0.538)	-0.167 (0.506)	-0.046 (0.498)	-0.293 (0.498)	-0.305 (0.538)	-0.167 (0.506)
2a	0.514 (0.355)	-0.194 (0.383)	-0.067 (0.368)	0.341 (0.367)	0.514 (0.355)	-0.194 (0.383)	-0.067 (0.368)
2c_gen	0.672 (0.381)	-0.489 (0.432)	0.218 (0.398)	0.073 (0.401)	0.672 (0.381)	-0.489 (0.432)	0.218 (0.398)
2c_voc	0.871* (0.355)	-0.048 (0.383)	0.272 (0.367)	0.643 (0.367)	0.871* (0.355)	-0.048 (0.383)	0.272 (0.367)
3a	1.391*** (0.357)	0.280 (0.384)	0.740* (0.368)	0.797* (0.368)	1.391*** (0.357)	0.280 (0.384)	0.740* (0.368)
3b	1.811*** (0.354)	0.424 (0.379)	1.064** (0.364)	0.847* (0.364)	1.811*** (0.354)	0.424 (0.379)	1.064** (0.364)
N	5254	5254	5253	5250	5253	5255	5207

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ **Appendix 5:** Polychoric correlation matrix of digital assistance systems items.

	1	2	3	4	5	6	7
1. Text/Speech	1.000						
2. Images/Videos	0.574	1.000					
3. Knowledge	0.649	0.596	1.000				
4. Data/Diagnoses	0.458	0.496	0.615	1.000			
5. Instructions	0.303	0.347	0.399	0.540	1.000		
6. Wearables	0.261	0.343	0.305	0.294	0.357	1.000	
7. Cobots	0.110	0.224	0.158	0.311	0.268	0.328	1.000

N = 5,245.

Appendix 6: Rotated factor loadings for digital assistance systems items.

Interpretation: Factor 1 primarily captures cognitively oriented digital assistance systems, while Factor 2 captures more manual or hardware-based applications.

	Factor 1	Factor 2	Uniqueness
Text/Speech	0.842		0.282
Images/Videos	0.790		0.362
Knowledge	0.878		0.228
Data/Diagnoses	0.724		0.369
Instructions	0.500	0.506	0.494
Wearables		0.640	0.482
Cobots		0.820	0.317
Eigenvalue	2.997	1.469	
Proportion of variance	0.428	0.210	
Cumulative proportion	0.428	0.638	

Note: Exploratory principal-component factor analysis based on the polychoric correlations matrix. Oblimin rotation. Loadings < |0.40| suppressed. N = 5,245.