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ABSTRACT

The Digital Gender Divide in Germany: The Role of Preferences and Constraints in Digital Involvement and Wages

This paper investigates the digital gender divide (DGD) in Germany by analyzing gendered patterns of digital technology use in both private and professional contexts, and their consequences for wages. Using data from the GESIS Panel, we construct a Digital Involvement at Work index covering ten technologies to assess both active use and passive exposure. Our results reveal a significant DGD in the workplace: women are consistently less involved with digital technologies at work, even after controlling for education, occupational qualification, and digital affinity. In contrast, private digital use appears more balanced. This suggests that structural constraints—rather than individual preferences—play a key role in shaping the divide. Further, we find that digital involvement is positively associated with individual income, yet it does not close the gender pay gap (GPG). On the contrary, digital involvement yields greater wage returns for men than for women. These findings highlight how gendered patterns of digitalization in the workplace reinforce existing inequalities. We conclude with a discussion of the implications for policy and labor market equity, emphasizing the need for measures that promote equitable digital inclusion.

JEL Classification: J31, J16, O15

Keywords: digitalisation, digital involvement, gender, wages, gender pay gap, Germany

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1. Introduction

Digital technologies have become integral to modern working life. They promise increased efficiency, productivity, and access to information, offering substantial advantages, including higher wages, greater social inclusion, and improved access to resources and networks (Aksoy et al., 2021; Brynjolfsson & Hitt, 2000). At the same time, digitalization can impose new forms of stress, increase exposure to surveillance, and diminish workers' autonomy and privacy (Holland et al., 2015; Payne, 2018; Stark et al., 2020). If women and men are unequally exposed to digital technologies—whether in terms of opportunities for use or risks of control—digitalization may inadvertently reinforce existing social inequalities (Acilar & Sæbø, 2023; Aksoy et al., 2021).

This paper investigates the extent to which working women and men in Germany use or are exposed to digital technologies differently. Understanding this so-called digital gender divide (DGD) is essential, since unequal involvement in digital processes can shape not only short-term productivity and access to training, but also long-term career development, labor market resilience, and income trajectories (UNESCO, 2024). In this context, DGD refers not only to differences in digital skills or internet access, but also to disparities in active usage and passive exposure to technologies in everyday work and private life.

While the DGD has received growing attention, prior research has often approached it in limited ways. One strand focuses on occupational segregation—highlighting, for example, women's underrepresentation in ICT or STEM-related fields (Lechman & Popowska, 2022; Papastergiou, 2008). Another stream examines gender differences in access to or self-assessed proficiency with selected technologies, especially the internet (Bachmann & Hertweck, 2025; Hargittai & Shafer, 2006). However, these approaches tend to overlook two critical dimensions. First, women outside tech-centric occupations - such as in healthcare, administration, or retail - also engage with digital technologies regularly. Second, previous work has largely failed to incorporate both, active technology use (e.g., software programs, apps etc.) as well as technology exposure – such as engagement with technologies by being tracked or monitored (e.g., location tracking or surveillance cameras). Active technology use is more visible and, thus, perceived more consciously in work environments. However, passive technology exposure should not be neglected since these technologies are also embedded in the workplace, yet, not actively used by employees (Holland et al., 2015; Stark et al., 2020).

In this paper, we broaden the concept of DGD by analyzing a comprehensive range of technologies, in both private and professional contexts. The investigated technologies cover both dimensions of technology involvement – those technologies that individuals actively use regularly as well as those that they are regularly exposed to. Using high-quality, representative data from the GESIS Panel, we provide the first population-wide analysis of gender differences in digital technology usage in Germany. Germany is a particularly relevant case for studying the digital gender divide. As a leading industrial economy with a strong manufacturing base and a rapidly expanding digital services sector, it exemplifies the challenges and opportunities of digital transformation in highly developed labor markets. Moreover, Germany's relatively traditional gender norms in employment make it a critical case for examining how digitalization interacts with already existing labor market inequalities. Our approach captures technologies as diverse as video communication, monitoring systems, security applications, and location tracking—offering a nuanced view of how digitalization shapes men's and women's work experiences.

We make four main contributions. First, we describe the raw DGD in Germany using a technology usage index that spans ten digital technologies. Second, we disaggregate this gap by type of technology and domain of usage (work vs. private life). Third, we explore potential explanations for the observed gaps, distinguishing between self-selection and structural constraints (Baumgart et al., 2023; Blickenstaff, 2005). Finally, we contribute to the Gender Pay Gap (GPG) literature by examining how digital technology usage correlates with individual wages. As previous work suggests, digital involvement may affect wages through increased productivity and skill requirements (Aksoy et al., 2021; Brown & Campbell, 2002), but these benefits may not be equally accessible to men and women.

By incorporating various technologies to cover active and passive digital exposure, linking professional and private domains, and incorporating labor market outcomes, our study offers a comprehensive picture of how digitalization intersects with gender inequality. In doing so, it not only refines existing understandings of the DGD but also provides an empirical basis for more equitable digital and labor market policies.

2. The Digital Gender Divide: What Do We Know?

This chapter provides a structured overview of existing literature on the digital gender divide (DGD), focusing on key dimensions including occupational segregation, digital skills, involvement (active and passive), private use patterns, mechanisms (self-selection vs. barriers), and the consequences of digital inequality (see also Abendroth et al., 2024; Acilar & Sæbø, 2023; Verwiebe et al., 2023).

2.1 Gender Differences in Occupations Requiring Digital Competencies

One common approach to studying the DGD is examining gender representation in occupations that require high levels of digital skills. A recurring finding is that women remain underrepresented in technology-intensive roles, particularly in STEM and ICT professions (Brussevich et al., 2018). Young et al. (2023) report that women are more likely than men to occupy a job associated with less status and pay in data science and AI fields. Lechman and Popowska (2022) show that despite some progress in tertiary education enrollment, gender disparities persist in high-tech employment across Europe. Women's participation in digitally intensive occupations remains substantially lower than men's, especially in advanced digital sectors. Piasna and Drahokoupil (2017)argue that digitalization tends to reinforce existing gender inequalities by restructuring labor markets in ways that favor male-dominated occupations. They emphasize that even new digital job forms (e.g., gig work) are not inherently gender-neutral but shaped by prior segmentation.

2.2 Digital Skills and Competencies

Beyond occupational roles, digital competencies are a critical factor shaping digital participation and outcomes. In a systematic review, Sánchez-Canut et al. (2023)highlight how digital skills have become fundamental for professional development—and how women's lower measured or perceived digital competence restricts their labor market opportunities. Franken and Wattenberg (2019)confirm this for young professionals in Germany, showing that men rate their own digital skills significantly higher than women, even when objective measures suggest no major difference. Indeed, several studies highlight that the gender gap in digital skills is often one of perception rather than performance. Hargittai and Shafer (2006) find no significant gender gap in actual online abilities but did observe that women report lower self-assessed digital competence, which in turn shapes their digital behavior and engagement. Lucas et al. (2022)reinforce this pattern, showing that gender differences in digital proficiency among university students are more about confidence and self-perception than measured competence. Overall differences regarding ICT skills between genders seem to have diminished over time (Acilar & Sæbø, 2023; Hargittai & Shafer, 2006).

Evidence from Germany further shows how the digital skills gap evolves over the life course. Using NEPS data, Bachmann and Hertweck (2025) find no significant gender difference in digital literacy in lower secondary school but a growing divide from upper secondary education onward. Factors such as unequal access to digital devices, gendered self-concepts, and academic field choices contribute to this gap.

2.3 Digital Involvement

Research on digital involvement focuses on both, active use of and passive exposure to technologies. In terms of active use, the increasing relevance of internet-based technologies has sparked substantial research on internet access and usage (Fatehkia et al., 2018; Gray et al., 2017; Scheerder et al., 2017). Studies suggest that the gender gap in internet use has narrowed over time. The International Telecommunication Union [ITU] (2024) reports a relatively small global divide for 2024: 70% of men versus 65% of women have used the internet recently. Bünning et al. (2023) show that among older adults in Germany, women have caught up with—or even surpassed—men in using the internet for communication and social connection, although men still lead in activities such as online banking and entertainment. López-Martínez et al. (2011) similarly observe limited gender differences in overall internet use and online purchases across EU countries, though some national variation persists. Franzen (2003), analyzing Swiss panel data, found that while women lagged behind men in internet adoption in the late 1990s, by the early 2000s they had largely closed the gap—suggesting that digital access inequalities can be overcome under favorable structural conditions. These findings indicate a convergence in basic digital use; however, functional and task-specific disparities remain (Haight et al., 2014). Moreover, gender inequality remains in less developed countries (e.g., Rashid, 2016).

On the other hand, in the DGD literature little attention is given to digital involvement regarding passive exposure to technology, particularly in the form of digital surveillance. So far, digital surveillance in work settings has been issued mainly by the EPM (electronic performance monitoring) literature regarding the acceptability and/ or effects on performance and other job aspects like OCB, trust or job satisfaction (e.g., Jeske & Santuzzi, 2015; Ravid et al., 2020; Stanton, 2000). However, reliable data on the gendered prevalence of workplace surveillance is limited (Parkes, 2023). Yet, qualitative and survey-based research reveals gender-specific responses. Stark et al. (2020) find that women are significantly less likely than men to approve of facial recognition technology in the workplace, citing concerns about privacy and autonomy. Payne (2018) shows that male supervisors in masculinized work cultures often use surveillance to perform competence and status, while women are excluded from these symbolic performances. Oz et al. (1999)report minor gender differences in beliefs about the effectiveness of electronic monitoring, and Holland et al. (2015)find no major gender-based differences in trust-related responses to surveillance, though occupational context appears to moderate perceptions.

Despite the limited availability of quantitative data on gendered surveillance exposure, the literature suggests that monitoring technologies are not experienced neutrally. Rather, they may reinforce existing gendered power dynamics in the workplace. Thus, effects of software encoded biases on gender (and racial) basis (Stark et al., 2020) and gender-specific perceptions of surveillance technologies might be overlooked if those technologies are neglected in the DGD debate.

2.4 Digital Technology Use in Private Life

While much of the literature on digital involvement focuses on the workplace, recent research also points to important gender differences in private ICT use. Bhandari (2019) shows that women internationally have lower access to mobile phone technology. Hu and Qian (2024) introduce the concept of a "digital double burden," showing that women across 29 countries are more likely than men to use ICT intensively for both professional and family purposes. Women are disproportionately "dual-high" users, combining job-related and domestic digital activities, whereas men are more likely to use technology for work alone. These findings suggest that digital inequalities intersect with traditional gender roles, shaping both work and non-work domains.

Christensen and Treas (2024)further highlight the gendered nature of digital technology use by showing that digital work contact contributes to work-to-family spillover, particularly for mothers. Drawing on data from 31 European countries, they find that while digital skills can reduce spillover overall, this buffering effect is weaker for mothers, who remain especially vulnerable to digital intrusions into family life. Their findings underscore how digital inequalities are reinforced by caregiving responsibilities and unequal boundary management capacities.

2.5 Self-Selection or Barriers?

A central question in the study of the digital gender divide (DGD) is whether gender gaps in technology use result primarily from self-selection or from structural barriers such as discrimination and exclusion. This distinction is crucial for policy: if preferences drive the gap, interventions should focus on individual orientation; if structural barriers are the main cause, systemic reforms are required. Most likely, both factors contribute, though their relative importance remains unclear.

Research shows that gendered educational and occupational pathways shape individuals' digital exposure. Blickenstaff (2005) argues that women's underrepresentation in STEM fields is not merely a matter of choice, but also a result of institutional bias. Papastergiou (2008) finds that girls' career intentions in computing are more strongly influenced by extrinsic factors and negative stereotypes than those of boys, which can have lasting consequences. Organizations further reinforce these dynamics. Baumgart et al. (2023) describe a "circulatory loop" in which digitalization and organizational practices co-produce gendered outcomes—often unintentionally—through management structures or biased algorithmic systems. Experimental evidence also confirms the persistence of symbolic barriers: Del Carpio and Guadalupe (2022) demonstrate that while targeted messaging can increase women's interest in tech careers, it often attracts applicants with weaker skills and more traditional beliefs.

Attitudes toward technology differ by gender as well. Borwein et al. (2024) find that women are less likely than men to perceive automation as fair, partly due to differing norms and perceptions of social status. Hilbert (2011) shows that, when controlling for education and employment access, women in developing countries actually use ICT more than men—highlighting the importance of structural constraints. In Germany, older women are less likely to participate in digital training despite comparable interest, pointing to organizational barriers (Kortmann et al., 2023).

Although the literature supports the relevance of both self-selection and structural barriers, the existing evidence is largely restricted to specific technologies or to narrow occupational and educational contexts.

2.6 Consequences of the Digital Gender Divide

The DGD has tangible consequences for women’s labor market outcomes, particularly regarding wages and employment stability. A growing body of research demonstrates that digital inequality—through restricted access to technologies, lower digital skills, or structural barriers to digital work—translates into lower earnings and greater job insecurity for women.

Several studies have shown that digital exclusion contributes directly to gender wage disparities. In a cross-country study for the European Union, Picatoste et al. (2023) found that gender gaps in digital access and skills correlate with broader earnings inequality. Specifically, women's limited participation in digital fields depresses their earnings quality, contributing to lower social welfare overall. Aksoy et al. (2021) find that robotization in Europe increases both men’s and women’s wages, but also widens the gender pay gap—primarily because men in medium- and high-skill jobs benefit more from automation. This indicates that digital technologies can reinforce structural wage disparities if access to digital work is uneven.

Research in the context of digital labor platforms echoes these findings. Han et al. (2024) show that digitalization in China’s gig economy has exacerbated gender wage gaps, with female gig workers earning significantly less than their male counterparts. Notably, this disparity was most pronounced for married and older women, and decomposition analyses revealed that the gap was largely unexplained by observed characteristics—suggesting discrimination. These studies collectively imply that while digitalization creates new economic opportunities, it may reinforce existing wage inequalities if women are systematically excluded from or devalued within digital labor markets.

The DGD also affects employment prospects and stability. In their study, Genz and Schnabel (2023) used linked employer–employee data from Germany to assess the impact of digital technology introduction on incumbent workers. Their findings show that women experience significantly greater employment loss than men—measured in both increased unemployment spells and lower days employed—after digital technologies are introduced in their workplace. The effects are particularly severe for women in non-routine occupations, suggesting that task allocations intersect with digitalization to heighten employment vulnerability.

Other global studies confirm the positive effects of digital inclusion on women’s labor market participation. In a panel study of 48 African countries, Ngoa and Song (2021)find that improved ICT access significantly boosts women’s labor force participation, especially when accompanied by broader developmental measures such as education and financial inclusion. Similarly, in China, Lu et al. (2023) show that the expansion of the digital economy has created new employment opportunities for women, particularly in roles aligned with women’s existing skills or social expectations. These gains, however, were not uniformly distributed: women with caregiving responsibilities benefited less, and digitalization did not necessarily reduce gender gaps in job quality or security.

In sum, while digitalization holds the potential to promote women's employment and earnings, current evidence suggests that the DGD continues to contribute to persistent gender inequalities. Bridging this divide is essential not only for enhancing individual labor market outcomes but also for fostering inclusive economic growth.

2.7 Defining the research gap

The existing literature on the DGD has made significant strides in identifying gender disparities in digital technology access, skills, and usage (see Abendroth et al., 2024; Acilar & Sæbø, 2023). However, it has done so primarily through two narrow lenses: occupational segregation—such as the underrepresentation of women in STEM and ICT roles—and the use of specific technologies, most commonly internet access. While these approaches have yielded important insights, they risk overlooking the full complexity of digital engagement in contemporary work and life.

This narrow focus creates several limitations. First, it ignores that women may engage with digital technologies in a variety of non-technical occupations where digital tools are increasingly embedded. Second, by concentrating on individual technologies, studies often miss the broader patterns of digital exposure—some technologies may be over- or under-represented depending on gender, domain (work vs. private life), or life course stage. Third, prior research on the DGD often centers on actively used technologies, neglecting gender disparities driven by passive exposure to digital technologies—particularly in the form of workplace surveillance, algorithmic management, and monitoring systems.

Taken together, these gaps highlight the need for a more comprehensive and differentiated approach to studying the DGD—one that captures a wider array of technologies, includes both active and passive forms of digital involvement, and considers both professional and private domains. Addressing these omissions is essential for developing a more accurate and policy-relevant understanding of how digitalization shapes gender inequalities in the labor market.

3. The DGD in Germany

3.1 Data Basis: The GESIS Online Panel

We use data from the GESIS Online Panel, a long-running, probability-based, mixed-mode panel survey of the adult population in Germany. The panel is maintained by the GESIS – Leibniz Institute for the Social Sciences and serves as an open-access research infrastructure for empirical social science research (Bosnjak et al., 2018).

Panel Design and Sampling

In the GESIS Panel respondents are recruited through probability sampling from population registers and conducts quarterly surveys. Participation is possible either via web surveys or postal questionnaires, allowing inclusion of both online and offline segments of the population. As of 2024, the panel includes five recruitment cohorts (2013, 2016, 2018, 2021, and 2023), yielding a balanced and representative cross-section of the German-speaking adult population. The 54th regular wave, labeled Wave "la", was fielded between February and April 2024, with 5,469 active panel members invited to participate. Of those, 4,282 were invited in the online mode and 1,187 in the offline mode. The fieldwork concluded in mid-April 2024. In the end, the sample results in 4,980 respondents. For our analysis which is focused on the role of digital technology at work we exclude all non-working respondents. Hence, our final dataset holds 2,573 observations from the panel year 2024 (wave "la") (Stadtmüller et al., 2025).

Figure 1: Instrument for sampling digital technologies (own translation)

Active use: "Which of the following digital technologies do you currently use regularly (i.e., at least once per week)?"

- Programs or apps for video-based communication
- Programs or apps for analyzing security risks
- Programs or apps you had to familiarize yourself with to process information or data
- Programs or apps for electronic control or granting of security clearances and access
- Security cameras used by me to monitor house entrances, properties, or other premises
- Applications for locating other people
- Programs or apps for spreadsheets, financial, or tax calculations

Passive exposure "Are you regularly (i.e., at least once per week) affected by the following digital technologies used by others?"

- Monitoring of your computer activities by other persons
- Monitoring by external security cameras
- Location tracking by others (e.g., smartphone, vehicle, smartwatch, etc.)

Both sets of items used the same four-point response format:

- Regularly used/affects me **both privately and professionally**
- Regularly used/affects me **only privately**
- Regularly used/affects me **only professionally**
- **Not used/does not affect me regularly or not at all**
- **Don't know**

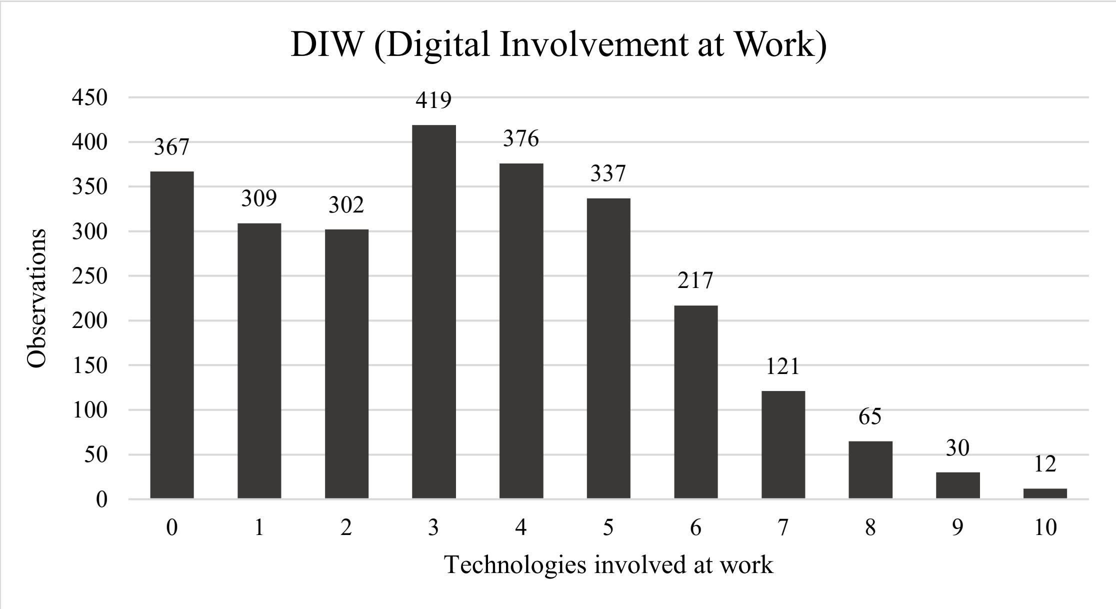
All analyses are based on weighted data using the design weights provided by the GESIS Panel. These weights account for varying inclusion probabilities across the three panel cohorts (2013, 2016, and 2018), as well as for disproportional sampling strategies (e.g., oversampling in Eastern Germany). Applying these enables population-representative inferences for the adult residential population in Germany aged 18 and older (Kolb et al., 2022).

Survey Instrumentation

For this study, we implemented a set of 16 questions in the GESIS Panel survey (Study "em" in Wave "la") prior to the field phase. Our questionnaire unit aims to assess digital technology use across multiple domains and modalities as well as general attitudes towards technologies. We introduced 10 technology types that differ in terms of engagement levels – either using technologies actively (active technologies: 7 items) or being exposed to technologies by being within their application sphere (passive technologies: 3 items). Figure 1 shows the instrument.

Based on this instrument, we constructed an index of Digital Involvement at Work (DIW), which counts the number of technologies a respondent uses either both privately and professionally or exclusively professionally. Thus, the index captures whether a digital technology is relevant in the respondent's work context, while not excluding additional private use. Figure 2 displays the distribution of this index.

Figure 2: Distribution of DIW Index



Additional Variables

Our analysis includes a set of covariates capturing key demographic and occupational characteristics. Analyzing effects of gender (male/ female), we control for respondents' age, school certificates (general/ intermediate/ higher secondary school), occupational qualification (vocational training/ tertiary education), industries, and weekly working hours. In terms of the Digital Gender Divide (DGD) we look at our DIW index (ranging from 0 to 10). Regarding the Gender Pay Gap analyses (GPG) we focus on respondents' personal net income (in 9 categories). We display all variables in the sample description (see Table 1).

Table 1: Sample Descriptives (only Employed Respondents)

Sample Descriptives (only Employed Respondents)	**N**	**Mean/ Proportion**	**Std. Dev.**	**Min**	**Max**
Age (in years)	2571	49.55	10.64	29	66
Sex	2568				
Male	1323	51.52			
Female	1245	48.48			
Education: School Level	2565				
General Secondary School or Lower	206	8.03			
Intermediate Secondary School	816	31.81			
Higher Secondary School	1543	60.16			
Occupational Qualification					
Vocational Training	1152	47.92			
Tertiary Education (Univ.)	1252	52.08			
Personal Net Income	2434				
up to 500€	10	0.41			
500€ up to 900€	58	2.38			
900€ up to 1500€	289	11.87			
1500€ up to 2000€	368	15.12			
2000€ up to 2600€	561	23.05			
2600€ up to 3200€	380	15.61			
3200€ up to 4000€	366	15.06			
4000€ up to 5000€	203	8.34			
5000€ and more	199	8.18			
Weekly Working Hours	1973	35.56	7.52	10	80
Industrial Affiliation	2155				
Construction and Mining	119	5.52			
Energy and Water Supply	55	2.55			
Service Industry	498	23.11			
Upbringing and Education	207	9.61			
Catering, Lodging, and Gastronomy	39	1.81			
Health- and Social Care	320	14.85			
Trade; Maintenance/Reparation of Motor Vehicles and Consumer Goods	115	5.34			
Information and Communication	120	5.57			
Agriculture, Fishery and Fish Farming	32	1.48			
Public Administration, Defense, Social Security	265	12.3			
Processing Industry, Production of Goods	288	13.36			
Traffic and Storage	97	4.5			
Technology Affinity	2165				
No Technology Affinity	334	15.43			
low Technology Affinity	570	26.33			
moderate Technology Affinity	694	32.06			
high Technology Affinity	567	26.19			
Technology Interest	2169				
(rather) high interest	1420	65.47			
neutral/no interest	749	34.53			
DIW (Index: Digital Involvement at Work)	2555	3.29	2.30	0	10
DIP (Index: Digital Involvement in Private)	2555	3.62	2.02	0	10
OWT (Index: Only Work Technologies)	2555	0.99	1.17	0	7
OPT (Index: Only Private Technologies)	2555	1.32	1.41	0	10

3.2 Use of digital technologies in the German workforce

This section examines how the German workforce engages with digital technologies, both in the context of work and private life, using representative survey data from the GESIS Panel. We aim to provide first evidence on the breadth and structure of digital technology use in Germany and explore gender differences in digital involvement. We complement the descriptive overview with a differentiated look at the learning of new digital technologies, the engagement with digital surveillance technologies, the usage context (work vs. private life), and the relevance of industrial affiliation. Table 2 provides a summary of the prevalence by domain of use for the technologies under study.

Technology Use: Overall Patterns

Across all technologies surveyed, we observe a relatively high level of digital engagement. However, about 14% (N=367) of respondents reported to not use any of the 10 proposed technologies at work (see Appendix, Table A1). As shown in Table 2, video communication tools, security applications, and data processing software are the most frequently used, with between about 13% and 23% of respondents indicating no regular use of these technologies. Conversely, tools such as calculation software (e.g., spreadsheet programs like Microsoft Excel) are used regularly by only about half of respondents. The surveillance technologies indicate that a little more than half of the respondents are not exposed to surveillance on a regular basis. However, about 22% of the respondents are exposed to computer monitoring and 18% to security cameras only at work. Contrary, location tracking seems to be more commonly used regularly only in private (12% of respondents).

Learning New Technologies

Digital technology use is not static. As a baseline, about 65% of respondents reported a (rather) high interest in new digital technologies in general. As shown in Table 2, approximately half of the respondents also indicated that they had learned to use a new digital technology within the three months preceding the survey. This high level of change highlights the need to consider the digital divide not only in terms of current access or skills but also in terms of the capacity for ongoing learning and adaptation.

Digital Monitoring: Low but Relevant

While some technologies support the dual-use of digital tools, others are more common in either work or private everyday life. Overall, digital monitoring technologies such as security cameras and tracking systems show much lower rates of regular use. Further, specifically monitoring technologies seem to depend on life domains. While security cameras are used actively more often in a private context (ca. 12%), (passive) exposure to security cameras is more common in the work context (ca. 18% of respondents). On the contrary, digital monitoring and location tracking indicate a domain-specific use in both – active use and passive exposure. While digital monitoring is used either only at work (15%) or at least also at work (20%) most respondents who are exposed to digital monitoring are monitored only at work (22%). On the other hand, location tracking is used actively (20%) and passively (12%) mainly in private. While not as pervasive as communication tools, monitoring technologies are nonetheless a salient feature of the digital work environment and merit attention due to their implications for privacy and control.

Usage Context: Work vs. Private Life

As previously shown, technology involvement is not just dependent on the type of technology but also on the context or domain. Table 2 illustrates the proportions of respondents using selected technologies for work only, private use only, or both. Especially for surveillance technologies (e.g., digital monitoring, security cameras, location tracking) respondents show differences in terms of the involved life domains (work vs. private). For example, 46% of users report using video communication tools in both domains, 18% use them only privately, and 12% only for work. The remaining 23% do not use them regularly. Similar patterns emerge for security software, which is used by a majority in both contexts. These findings underscore the dual-use nature of certain digital tools and their increasing ubiquity in everyday life.

Table 2: Technology usage by domain

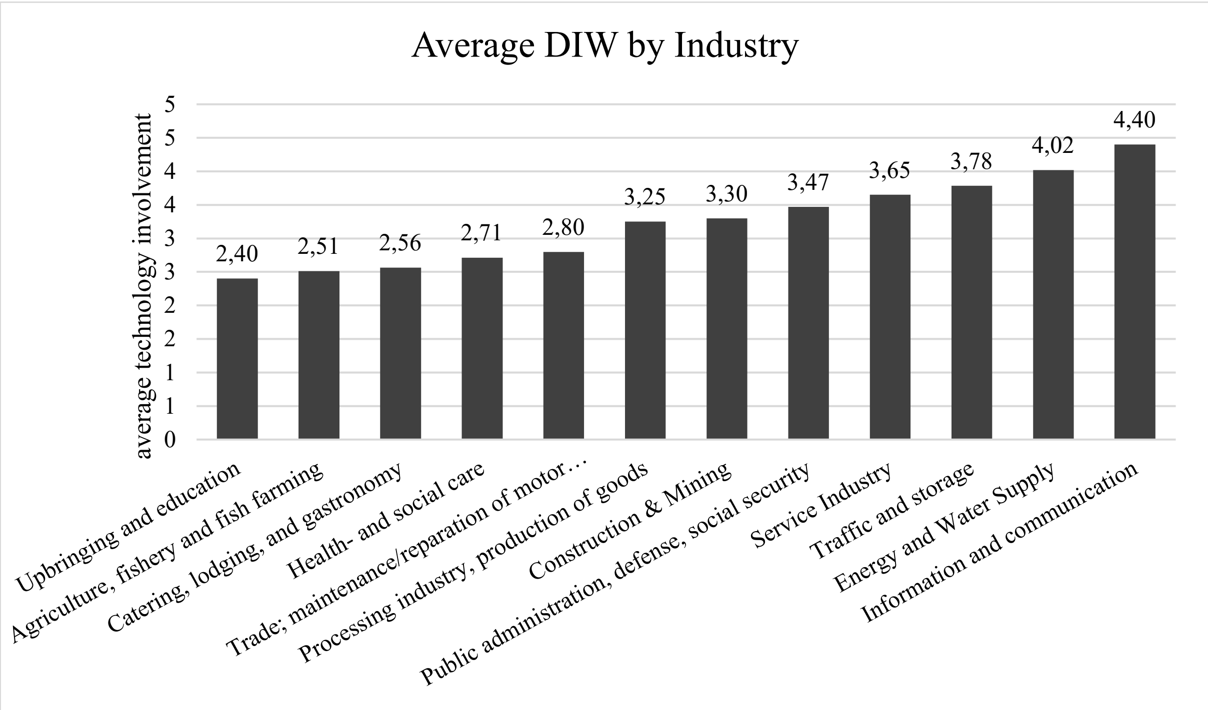
Technology is used…											
Tech Type	**private and work**		**only privately**		**only at work**		**not regularly**		**don't know/mv**		**Total**
	N	%	N	%	N	%	N	%	N	%	N
Use of…											
video communication	1173	*45.59*	463	*17.99*	305	*11.85*	584	*22.70*	48	*1.87*	2573
security software	1366	*53.09*	390	*15.16*	209	*8.12*	426	*16.56*	182	*7.07*	2573
data processing software	1290	*50.14*	778	*30.24*	101	*3.93*	330	*12.83*	74	*2.88*	2573
digital monitoring	501	*19.47*	195	*7.58*	380	*14.77*	1236	*48.04*	501	*19.47*	2573
security cameras	134	*5.21*	310	*12.05*	129	*5.01*	1900	*73.84*	100	*3.89*	2573
location tracking	190	*7.38*	505	*19.63*	41	*1.59*	1747	*67.90*	90	*3.50*	2573
calculation software	720	*27.98*	277	*10.77*	263	*10.22*	1218	*47.34*	95	*3.69*	2573
Exposed to…											
computer surveillance	138	*5.36*	48	*1.87*	559	*21.73*	1402	*54.49*	426	*16.56*	2573
security cameras	225	*8.74*	117	*4.55*	463	*17.99*	1414	*54.96*	354	*13.76*	2573
location tracking	142	*5.52*	298	*11.58*	89	*3.46*	1700	*66.07*	344	*13.37*	2573
learning new tech (last 3 months)	640	*24.87*	250	*9.72*	425	*16.52*	1151	*44.73*	107	*4.16*	2573

If respondents are involved with technologies respondents usually engage with them in both domains (see Appendix, Table A1). However, about 28% of respondents use at least one technology exclusively in one domain – either work or in private. Almost half of the respondents (45%) are not using any of the technologies only at work and about 35% of respondents are not engaging with any of the technologies only privately (see Appendix, Table A1).

Workplace Technologies: Digitalisation Across Industries

For our following analysis we used the standard classification of industries and merged some of the original categories based on (see Appendix A2 for details). Based on the resulting 12 industrial sectors we calculated the average DIW across all respondents for each sector (see Figure 3). So far, the potential and/or degree of (workplace) digitalisation among industries has been hard to grasp. As a first proxy to indicate technology variety across industries we, therefore, calculated the average amount of technologies – based on our 10 technology items – for each sector. Figure 3 displays the average number of technologies respondents within an industry use at work or at work and privately (mean DIW by industry). As expected, gastronomy and agriculture exhibit low levels of digitalization, whereas the information and communication sector scores the highest. However, the mean DIW can only serve as a vague proxy for the digitalization degree across sectors without further specification what kind of technologies are used. It is likely that some industries might be more prone to certain technologies than others. For example, the Traffic and Storage sector might be more penetrated by monitoring technologies while the Service Industry might engage more in communication and calculation software tools.

Figure 3: DIW Index by Industry



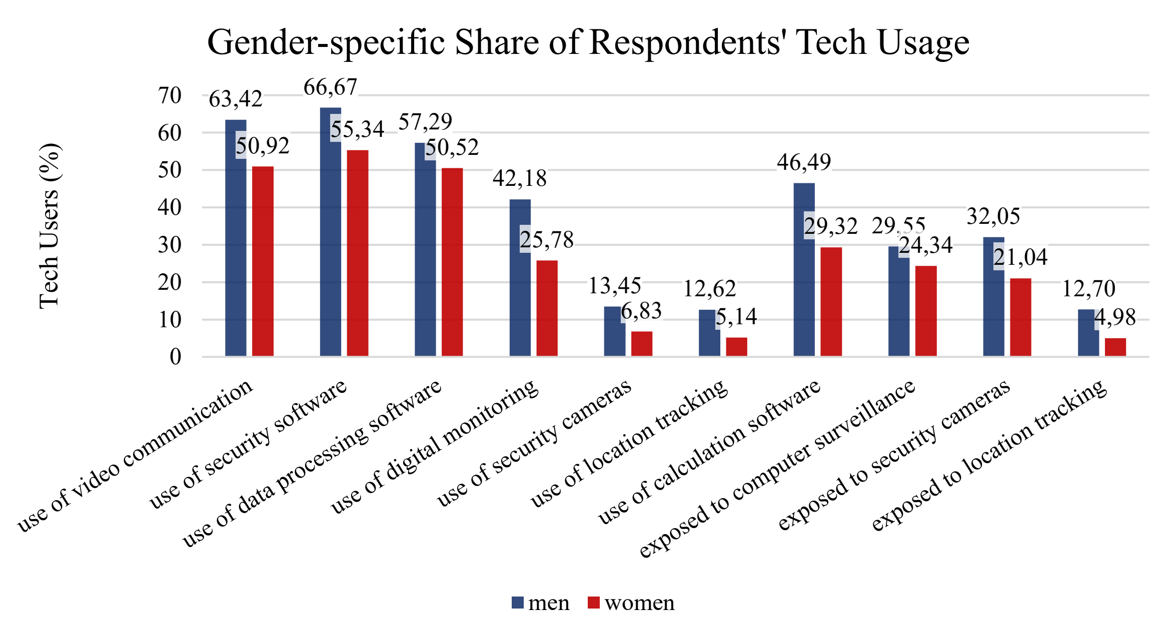
3.3 Gender Differences in Digital Involvement at Work?

This section examines gender differences in the use of digital technologies at work, drawing on descriptive and multivariate evidence from the GESIS Panel. We focus on those respondents who report that digital technologies are used either exclusively at work or both at work and in private life. This operationalization captures professional digital involvement and allows us to measure what we term the "raw digital gender divide" (raw DGD)—that is, unadjusted differences in reported usage by gender.

Descriptive Patterns: Raw Gender Differences in Use

The first and most striking finding is that women are significantly less likely than men to use digital technologies in their professional lives. Figure 4 illustrates this pattern descriptively across all technologies: When considering the gender-specific share – that is, the proportion of men (women) using a certain technology out of all male (female) respondents – similar usage patterns emerge for both genders. However, men consistently report higher usage levels within their group across all technologies. Notably, only three technologies are regularly used at work by more than half of the female respondents: video communication platforms, security software, and information or data processing tools. For all other technologies—including spreadsheet applications, access control systems, and surveillance tools—regular usage among women remains below 50%.

Figure 4: Gender-specific Share of Respondents' Tech Usage



Overall, these descriptive results suggest a broad and consistent pattern: women are less digitally involved at work, both in terms of breadth (number of technologies) and frequency (regularity) of use.

Multivariate Analysis: Adjusted Gender Differences

To examine whether the DGD persists after accounting for relevant background factors, we performed regression analyses using the composite index of digital involvement at work (DIW) as the dependent variable. We estimated OLS (Ordinary Least Squares) as well as OLogit (Ordered Logistic) regression analyses treating our dependent variable as continuously (OLS) or ordered-categorical (OLogit). We further estimated a Negative Binomial Regression (NegBin) regression. This estimation method suits the count data structure of our DIW index – consisting of the number of technologies respondents are engaging with (at least) at work. All three models yield similar results in terms of effect sizes and significance (see Appendix, Table A3). However, the NegBin Regression proves to be the most conservative model with overall lower significance levels. Relying on the more conservative model, we continue with the NegBin estimation and display IRRs (Incidence Rate Ratios) in the following part of the paper.

Our main descriptive result is also replicated in Table 3: Men show significantly higher digital involvement than women (Table 3, Model 1). To test whether the raw DGD can be accounted for by other parameters, we integrate several control variables in our regression analysis. We account for age, education level (school certificate), occupational qualification (vocational qualification vs. (higher) tertiary education), working hours (per week), and industrial sector. We additionally estimate a model controlling for self-reported digital affinity. We assume that self-reported digital affinity can be treated as a proxy for individual technology preferences. Thus, we use this variable as a first approach to distinguish preferences (self-selection) and discrimination regarding gendered use patterns of (work) technologies.

The results confirm that the gender effect remains statistically significant (see Table 3, the full model including controls can be found in A4): men are still significantly more likely than women to report regular involvement of digital technologies at work, even after adjusting for several covariates (Table 3, Model 2-4). While the null model suggest that men's technology involvement rate is on average about 37% higher than women's (IRR=1.347) this effect decreases but remains persistent over all models (Model 4: IRR=1.134). In other words, the observed gender gap cannot be fully explained by differences in age, qualification (school and occupational) (Table 3, Model 2), occupational factors (working hours and industry; Table 3, Model 3), or general affinity for technology (Table 3, Model 4). This finding highlights the robustness of the digital gender divide and suggests that structural and cultural factors may underlie the unequal distribution of digital tasks and responsibilities in the workplace.

Table 3: Negative Binomial Regression on DIW

DIW (Digital Involvement at Work)	(1) Raw DGD	(2) Adj. DGD	(3) Adj. DGD	(4) Adj. DGD
Sex: Male (Ref.: Female)	**1.374** ***	**1.339** ***	**1.165** ***	**1.134** ***
	0.038	*0.038*	*0.042*	*0.040*
Control Variables:				
Age, School Degree, Occup. Education	--	*yes*	*yes*	*yes*
Working Hours, Industry	--	--	*yes*	*yes*
DIW, Technology Affinity	--	--	--	*yes*
N	2550	2377	1827	1823
AIC	11,000.000	10,000.000	7,573.878	7,468.094
BIC	11,000.000	10,000.000	7,722.659	7,633.341

DV: DIW index (11 categories: [0;10]); Estimation Results: Indcidence Rate Ratios from Negative Binomial Regression, Std.Err. below
Significance: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Technology-Specific Gender Gaps

Our statistical analysis of the DGD using our DIW index indicated a greater likelihood for men to be regularly involved with digital technologies in a work context compared to women. For a more nuanced picture of technology usage patterns, we estimated bivariate logistic regressions for each technology with the dependent variable "regular tech involvement at least at work: yes/no" (see Table 4, Model 1 "min. at work"). Thus, we aim to determine whether the DGD is a persistent overall pattern or rather depends on specific technology types.

The results confirm the descriptive picture: across all digital tools, men are more likely than women to be regularly involved with technologies in a work context (Table 4). However, the magnitude of the gender effect varies across technologies, as shown by the differing odds ratios. Further, data processing and calculation software technologies are the only digital tools that show no significant gender differences if they are used exclusively at work (Table 4, Model 3).

Table 4: Bivariate Logistic Regression, Gender Effect of Technology Involvement

Dependent Variables (by Techs)	(1) min. at work		(2) min. privately		(3) only at work	
	Odds Ratio	P>|z|	Odds Ratio	P>|z|	Odds Ratio	P>|z|
use of video communication	1.671	0.000	0.946	0.496	2.007	0.000
use of security software	1.614	0.000	1.417	0.000	1.324	0.055
use of data processing software	1.314	0.001	1.302	0.008	0.920	0.680
use of digital monitoring	2.100	0.000	2.097	0.000	1.302	0.018
use of security cameras	2.122	0.000	1.526	0.000	2.016	0.000
use of location tracking	2.666	0.000	1.233	0.019	2.049	0.034
use of calculation software	2.094	0.000	2.418	0.000	0.896	0.398
exposed to computer surveillance	1.304	0.003	1.299	0.089	1.209	0.049
exposed to security cameras	1.770	0.000	1.383	0.006	1.578	0.000
exposed to location tracking	2.775	0.000	1.091	0.409	3.158	0.000
N	2568		2568		2568	

Estimates from bivariate Logistic Regression (no controls)
Odds Ratios for Gender (Male, Ref.: Female)

When it comes to using technologies in a mainly work-related context (Table 4, Model 1), information and data processing programs show the smallest gender gap (OR=1.314), suggesting a more balanced distribution between men and women. This result is consistent with expectations, as these programs represent core tools used across many occupations and are often part of routine digital workflows. Yet, when it comes to technology exposure at work, an even slightly smaller gender gap is found for being exposed to computer surveillance tools (OR=1.304). Even though men are still more likely to be monitored digitally on their computers at work, screen tracking tools seem to be implemented rather similarly for men and women. However, the gender differences for these technologies disappear if we only account for exclusively work-related technology use (Table 4, Model 3). In contrast, the largest gender gaps appear in the use of location tracking technologies – both actively tracking and being tracked. Generally, surveillance technologies (digital monitoring and security cameras) also show similar strong gender differences. Consistent with gender associations of IT skills, we find a rather strong DGD for men's higher likelihood to use calculation software technologies. Thus, our results support our expectation that certain technologies – especially tools which are more prevalent in male-dominated technical or supervisory roles – show a greater gap between men's and women's technology involvement.

This technology-specific breakdown provides important nuance: while the general picture points to lower digital involvement among women, the extent of the divide depends on the function, context, and institutional embedding of the technology in question.

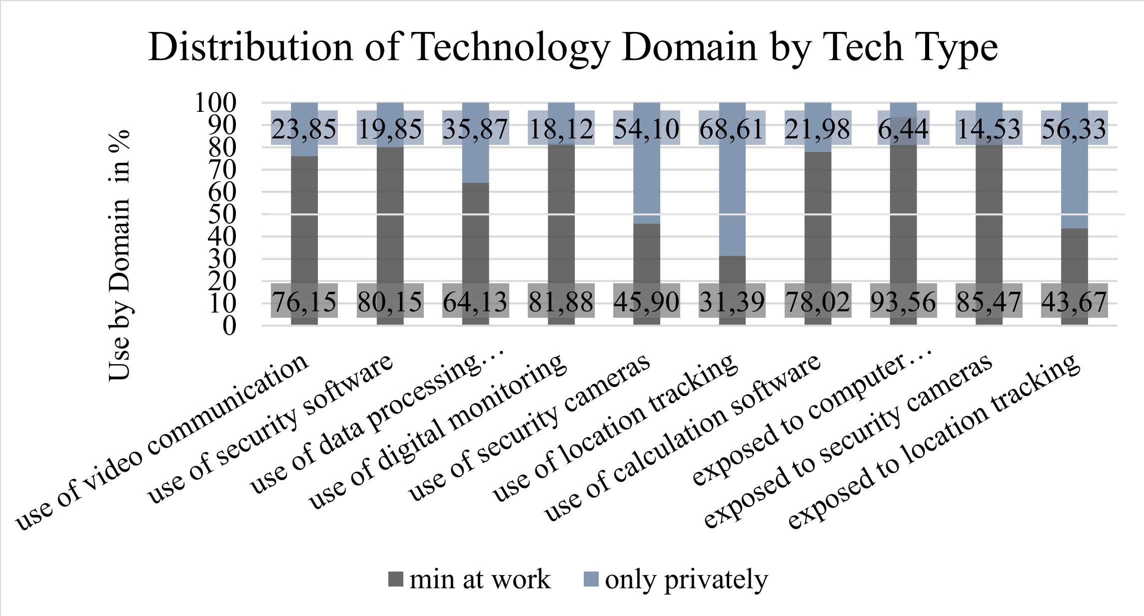
3.4 Preferences or Constraints? Interpreting the Digital Gender Divide

While previous sections have shown that women are significantly less involved in workplace technology use, the central question remains: Do women actively self-select into jobs with lower digital demands due to preferences, or are they systematically excluded or steered away from such jobs due to structural barriers and constraints?

To approach this question empirically with our representative data, we employ a two-step strategy: For a first test we compare gender differences in private versus work-related technology use, assuming that private use is shaped mainly by personal preference rather than institutional constraints. For a second test we control additionally for individuals' self-reported digital affinity in multivariate regressions. If gender differences in digital involvement persist even after accounting for interest in technology, this strengthens the argument for structural constraints.

Our first test builds on the idea that private use of digital technology reflects voluntary engagement, relatively free from workplace structures or job-based selection. In contrast, work-related digital use may be influenced by employers' technology adoption, job design, or gendered task assignments. If gender gaps are significantly larger in the work context than in the private context, this would suggest the presence of constraints.

Figure 5: Gender Effect for Tech Type by Use Domain



To test this conjecture, we estimate a series of bivariate logistic regressions for each digital technology (Table 5). The dependent variable is coded 1 if the respondent uses the technology at work (either exclusively or in both private and professional contexts), and 0 if it is used only in private life (see Figure 5). Respondents who report no use or are unsure are excluded to isolate those who actively engage with the technology. The key independent variable is gender (reference category: female).

Across all technologies, the odds of men using a given technology professionally rather than exclusively in private are significantly higher than those of women. For example, men are nearly twice as likely as women to use video communication tools at work compared to using them only privately ($OR = 1.819$, $p < 0.000$). As our previous analyses already showed, location tracking – both actively tracking others and being exposed to tracking – is significantly higher for men to a substantial degree. One explanation for this particularly strong effect for location tracking technologies might stem from the nature of job tasks that promote location tracking, such as transportation or work-related travelling. Especially jobs including (transportation) vehicles (e.g., trucks, planes, cars etc.) are typically male-dominated. Interestingly, computer surveillance technologies are the only type of technology without a significant gender difference. While men are still more likely to monitor others' computer activities at work ($OR = 1.400$, $p<0.036$) there are no significant differences between men and women of being exposed to computer monitoring at work ($p<0.258$). This result also aligns with the previously overall small gender effects for computer monitoring technologies. We presume that computer surveillance might be implemented more generally at work sites for all employees – independent of gender compositions. The significantly stronger effect for the active use of such tools might stem from the fact that leadership positions are male-dominated, making men more likely to be the monitoring parties.

Table 5: Bivariate Logistic Regression, Domain Differences of Gendered Technology Involvement

Dependent Variables (by Techs)	**min. at work (vs. only private)**		
	Odds Ratio	P>|z|	N
use of video communication	1.819	0.000	1936
use of security software	1.347	0.009	1961
use of data processing software	1.249	0.013	2165
use of digital monitoring	1.400	0.036	1074
use of security cameras	1.594	0.008	573
use of location tracking	2.758	0.000	735
use of calculation software	1.277	0.077	1256
exposed to computer surveillance	1.403	0.258	742
exposed to security cameras	1.763	0.005	803
exposed to location tracking	3.321	0.000	526

Estimates from bivariate Logistic Regression (no controls)
Odds Ratios for Gender (Male, Ref.: Female): involvement min at work (1) vs. involvement only privately (0)

The results support the hypothesis that selectivity is lower in private use: women are more likely than men to use digital tools exclusively in private life, while men dominate in professional contexts. This pattern indicates that the observed workplace digital gender divide is not simply a reflection of differing preferences but points to institutional or occupational constraints that limit women's digital involvement at work.

In the second step, we assess whether the DGD can be explained by differences in personal attitudes toward technology—specifically, self-reported technological affinity. If women use digital technologies less because they are less interested or comfortable with such tools, then controlling for technological affinity in a multivariate model should eliminate or substantially reduce the observed gender gap.

Our previous analysis already demonstrated that the raw Digital Gender Divide (raw DGD) (IRR=1.374) can be reduced by accounting for several influential factors—such as sociodemographic characteristics, occupational variables, and technology affinity—but nevertheless remains statistically significant across all models (Table 3). When controlling for all variables, we find a strong and highly significant effect of individual technology affinity (see Table 3, Model 4).

To further explore the robustness of our findings, we estimated models across different domains of technology involvement: (a) minimum involvement at work, (b) exclusive involvement at work, (c) minimum involvement in private life, and (d) exclusive private involvement (see Appendix, Table A5). These models reveal a significant gender effect across all domains, and except for the exclusively private domain (OPT index), a significant positive association between technology affinity and technology involvement. For the domain of exclusively private technology involvement (OPT index), the gender effect is reversed—indicating that women have higher odds than men of regularly using multiple technologies in private contexts only (see Appendix, Table A5, Model 4). In this model, technology affinity is no longer statistically significant. A descriptive look at the gender distribution of exclusively private involvement for each technology (Table 6) shows that for the private domain the involvement of almost all technologies is rather balanced. Interestingly, women are even dominating the share of regular users for most technologies – except for the use of digital monitoring, security camera, and calculation software. Especially the private use of video and communication technologies is rather female-dominated: About 58% of respondents who use this technology only privately are women (Table 6). Thus, the domination of male technology users in work-related domains doesn't seem to be rooted in private technology involvement or personal preferences. Even though the cases of exclusively private technology use are comparatively small this picture underlines the importance of investigating gender inequalities in more digitalized work places.

Table 6: Private Technology Involvement by Gender

Tech Involvement (only private): Yes	Men (%)	Women (%)	N
use of video communication	42.12	57.88	463
use of security software	48.72	51.28	390
use of data processing software	49.10	50.90	778
use of digital monitoring	55.38	44.62	195
use of security cameras	56.77	43.23	310
use of location tracking	48.61	51.39	504
use of calculation software	56.88	43.12	276
exposed to computer surveillance	47.92	52.08	48
exposed to security cameras	47.86	52.14	117
exposed to location tracking	44.93	55.07	296
Sum			2568

Overall, increasing technology involvement among individuals with greater technology affinity, and the persistence of the DGD, is observed across all work-inclusive domains. However, technology involvement in an exclusively private context indicates a different picture: Women are not less, but partly even more likely to use technologies. Thus, to investigate whether these effects stem from individual preferences or from structural constraints, we specified additional models with gender interaction terms. These interaction effects between gender and technology affinity were mostly insignificant (results not shown). A further model using a dichotomous indicator for (high) technology interest (versus neutral/no interest) also yielded no significant interaction effects (see Appendix, Table A6). This suggests that technology involvement at work does not differ significantly between men and women based on their level of technology interest. These findings further support the interpretation that preferences alone are unlikely to account for the DGD. Instead, structural or societal constraints appear to play a more decisive role.

Additional support for this interpretation comes from a comparison of marginal effects in a linear regression model (OLS) including an interaction term between gender and technology interest (see Table 7). As expected, individuals with higher technology interest are more likely to be regularly involved with digital technologies at work—this holds true for both men and women. However, the DIW index does not differ significantly between technologically interested women and technologically uninterested men ($p = 0.103$). We interpret this as evidence that, for women, stronger technology interest—or preferences—does not compensate for men's higher baseline level of technological involvement.

Table 7: Regression on DIW, Marginal Effects

DIW (Digital Involvement at Work)	**ME**	P>|t|	Δ	P>|t|
Gender: Female				
Tech Interest: No	**2.120**	0.000	**-1.082**	0.000
	0.087		*0.126*	
Tech Interest: Yes	**3.201**	0.000	*Ref.*	--
	0.091		--	
Gender: Male				
Tech Interest: No	**2.942**	0.000	**-0.260**	0.103
	0.131		*0.159*	
Tech Interest: Yes	**4.045**	0.000	**0.843**	0.000
	0.081		*0.122*	

Marginal Effects from Linear Regression Analysis
DV: DIW index (11 categories: [0;10]); Std. Err. Below

Taken together, these results point more toward structural barriers than to pure self-selection. The fact that women show equal or even higher digital involvement in private, and that controlling for technological affinity has little effect, undermines the preference-based explanation. In contrast, structural factors related to education and occupational roles explain a considerable portion of the gender gap. While self-selection into certain jobs may occur, it is likely shaped by employer practices, institutional norms, and broader societal expectations. Thus, the digital gender divide in professional settings cannot be reduced to individual choices alone.

4. Consequences of the Digital Gender Divide for Wages

In this final step, we turn to the economic implications of the DGD by examining how digital technology use affects individual income. Specifically, we investigate whether women's lower digital involvement at work contributes to the observed gender wage gap and whether digital technology use is rewarded with higher earnings.

The theoretical foundation for this analysis draws on human capital theory and wage-setting models, particularly the Mincer equation (Mincer, 1974). As Brown and Campbell (2002) argue, technological change can affect wages via two primary channels. First, active use of digital technologies may increase individual productivity, leading to higher earnings. Second, because digital tools often require specific skills and ongoing learning, employers may offer wage premiums to incentivize workers to acquire and apply these competencies. Taken together, these mechanisms imply a positive relationship between the extent of digital technology use and wage levels.

Empirically, we estimate ordered logistic regression models using monthly personal net income as the dependent variable. This variable is measured on a nine-point ordinal scale ranging from "up to 500€" to "5000€ and more" (see Table 1). The models estimate the probability of being in a higher income category, based on digital technology use and other individual characteristics. A first descriptive comparison reveals a clear unadjusted gender wage gap (raw GPG). Looking at the 50 percentiles, men earn 2600 – 3200€ while women earn 2000 – 2600€. More importantly, looking at the income distribution, women accumulate in lower income categories while men occupy the higher end of the income scale (see Figure 6). This difference reflects both structural labor market inequalities and, potentially, differences in digital engagement.

Figure 6: Income Distribution by Gender

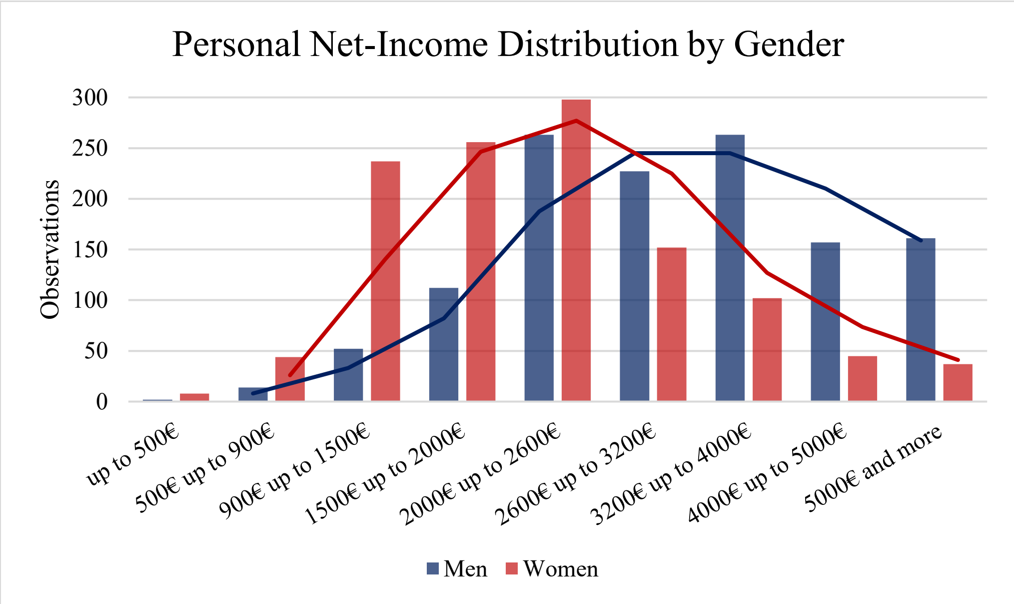


Table 8: Gender Pay Gap (GPG), Ordered Logit Regression on Personal Net Income

Personal Net Income	(1) Raw GPG	(2) Adj. GPG	(3) Adj. GPG	(4) Adj. GPG
Sex: Male (Ref.: Female)	**4.804** ***	**5.102** ***	**2.810** ***	**2.631** ***
	0.371	*0.422*	*0.292*	*0.281*
Control Variables:				
Age, School Degree, Occup. Education	--	*Yes*	*Yes*	*Yes*
Working Hours, Industry	--	--	*Yes*	*Yes*
DIW, Tech Affinity	--	--	--	*Yes*
N	2430	2274	1758	1744
AIC	9,177.138	8,147.644	5,786.285	5,617.351
BIC	9,229.299	8,222.125	5,923.084	5,775.805

DV: Personal Net Income (9 categories); Estimates: Odds Ratios from Ordered Logit Regressions, Std.Err. below
Significance: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

We specified four ordinal logistic regression models (see Table 8). The first model ("Raw GPG") reveals a highly significant unadjusted gender pay gap (GPG) with an odds ratio of 4.804, indicating that men have substantially higher odds of earning greater wages compared to women. In the subsequent models, we incrementally include additional sets of control variables: sociodemographic characteristics (age, educational attainment, and vocational qualification) in Model 2; occupational variables (working hours and industry) in Model 3; and finally, digitalization-related factors (DIW index and technology affinity) in Model 4. Although the GPG decreases across models—except in Model 2, where the inclusion of sociodemographic controls results in a slight increase—the gap remains consistently large and highly significant throughout (full models reported in Appendix Table A7).

The ordered logistic regression models confirm that gender remains a significant predictor of income, even after controlling for technology use and affinity. Women are less likely than men to be in higher income categories. To further examine the relationship between the digital gender divide (DGD) and the gender pay gap (GPG), we re-estimated the full model including an interaction term between gender and our Digital Involvement at Work (DIW) index (see Table 9). In both the baseline model without controls (Model 1) and the interaction model with full controls (Model 2), gender and digital involvement each show a significant positive association with income. Moreover, the interaction term is also significantly positive, suggesting that men with higher digital involvement are slightly—but significantly—more likely to earn higher wages compared to women with similar digital engagement. This pattern is further supported by the gender-specific models. Among women (Model 3), each additional digital technology used at work increases the odds of being in a higher income category by approximately 18%. For men (Model 4), the corresponding increase is about 29%. Thus, while digital technology use is positively associated with income for both genders, the returns appear to be greater for men.

Overall, individuals who regularly use a broader range of digital tools at work are more likely to earn higher wages. Technological affinity also shows a positive, albeit weaker, association with income.

Table 9: Gender-specific Effect of DIW on Wages

Personal Net Income	**(1) Base Model**	**(2) Interaction**	**(3) Only Women**	**(4) Only Men**
Sex: Male (Ref.: Female)	**3.998** ***	**1.925** ***		
	0.314	*0.320*		
DIW (Dig. Involvement Index)	**1.321** ***	**1.178** ***	**1.182** ***	**1.290** ***
	0.023	*0.036*	*0.039*	*0.006*
Interaction: Female # DIW (Ref.)				
Interaction: Male # DIW		**1.098** *		
		0.043		
Controls	*no*	*yes*	*yes*	*yes*
N	2415	1744	843	901
AIC	8,842.465	5,613.737	2,616.078	2,992.849
BIC	8,900.360	5,777.655	2,748.713	3,122.544

DV: Personal Net Income (9 categories); Estimates: Odds Ratios from Ordered Logistic Regressions, Std.Err. below
Significance: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001
Controls included: Age, School Degree, Occupational Education; Working Hours, Industry, Tech Affinity

Taken together, these findings indicate that digital involvement contributes to individual earnings and is economically rewarded. However, it does not reduce the gender wage gap. Even when accounting for digital skills and usage, women earn less than men. On the contrary, results from interaction analysis indicate that men profit even more from digital involvement at work compared to women in regard of wage increases. This supports the broader interpretation of the DGD as a structural issue: while digital technology use is beneficial, it is unevenly distributed across gender lines due to occupational segregation and differentiated task assignment. Women are not necessarily underpaid for using digital tools—but they are less often assigned to roles in which such tools are central to work. As a result, digital upskilling alone is unlikely to eliminate gender pay disparities.

5. Discussion and Conclusion

This paper set out to examine the digital gender divide (DGD) in Germany and its potential consequences for wages. By employing a novel instrument on the use of and exposure to digital technologies within the representative GESIS Panel, we go beyond existing measures and provide a comprehensive empirical picture of gender differences in workplace technology use. Furthermore, we investigate whether these differences reflect individual preferences or structural barriers, and assess how digital involvement translates into wage outcomes.

Our analysis confirms the existence of a substantial DGD in professional contexts. Across all ten types of digital technologies covered in our survey, women reported significantly lower levels of regular use at work, even though private use was generally more balanced between men and women. The gender divide persists after controlling for education, technology affinity, and industry, suggesting that it cannot be explained solely by individual preferences. Instead, it appears to be shaped by structural inequalities—such as task assignment and occupational sorting—that limit women's access to digitally intensive roles. Yet, we cannot rule out the inverse effect of digitalisation from the work domain to the private domain. Hence, technology involvement at work might translate or influence individual's familiarity and attitudes towards technology engagement in private. Low technology involvement at work may hinder technology use in private whereas high technology engagement at work may nudge higher private technology use.

With regard to wages, our findings show that digital technology use is positively associated with individual income for both men and women. Both, higher technology affinity and broader workplace technology use, increase the likelihood of being in higher wage categories. However, the gender pay gap remains statistically significant even after accounting for workplace digital involvement. This indicates that while digitalization helps explain part of the wage disparity, it does not fully account for it. Our results suggest that women's lower involvement with digital technologies at work may contribute to, rather than mitigate, the gender pay gap (GPG).

Despite the robustness of our findings, several limitations should be noted. First, the dataset lacks detailed information on occupational factors (e.g., firm size, corporate structure, employee representation, occupational roles, specific job tasks etc.). Although we control for education and industry, these proxies may not fully capture how job content shapes digital exposure. Second, our measure of technology involvement is based on regular use (at least once per week) and does not capture intensity, duration, or complexity of use. Additionally, all measures are self-reported and thus reflect only consciously perceived engagement with digital tools. As a result, subtle or unconscious forms of digital engagement may be overlooked. Third, our analysis is limited to wage outcomes and does not account for other factors that may also be affected by digital involvement, such as job security, job satisfaction, or career progression. Since personal net income was conducted categorically, nuanced income effects cannot be investigated. Further, household-related aspects (e.g., household members, children under the age of 16, and marital status) are not included in our regression models. However, regression analyses including those variables (household members, children under age of 16, and marital status) indicated robust results – indicating a similar (slightly bigger) GPG (results not shown). We excluded the household-related variables from our models since marital status should be somewhat accounted for in the income variable (net income includes marital status through tax classification). Further, the other variables didn't show consistent significant effects across the models.

Overall, the results suggest clear policy implications. The persistence of a substantial DGD in work-related digital use raises important concerns about fairness in an increasingly digitalized labor market. Even where direct wage effects are limited, indirect consequences—such as access to promotions, task autonomy, or upskilling opportunities—are likely and remain underexplored. Policy efforts should therefore pursue two central goals: first, to expand the empirical knowledge base on the broader consequences of digital exclusion; and second, to implement targeted measures aimed at reducing the DGD. This could include investments in gender-sensitive digital training, incentives for equitable task allocation during digital transformation processes, and support for women's access to digitally intensive occupations—especially in sectors undergoing rapid technological change.

In conclusion, the digital gender divide remains a relevant and persistent form of labor market inequality. Addressing it will require both improved data and more ambitious interventions to reshape the gendered structure of digital work.

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Appendix

A1: Technology usage by domain (II)

Techs	DIW (min work)		DIP (min private)		OWT (only work)		OPT (only private)	
	N	%	N	%	N	%	N	%
0	367	*14.36*	137	*5.36*	1139	*44.58*	894	*34.99*
1	309	*12.09*	219	*8.57*	714	*27.95*	714	*27.95*
2	302	*11.82*	402	*15.73*	426	*16.67*	499	*19.53*
3	419	*16.4*	552	*21.6*	180	*7.05*	267	*10.45*
4	376	*14.72*	455	*17.81*	61	*2.39*	99	*3.87*
5	337	*13.19*	353	*13.82*	23	*0.9*	49	*1.92*
6	217	*8.49*	221	*8.65*	10	*0.39*	17	*0.67*
7	121	*4.74*	121	*4.74*	2	*0.08*	8	*0.31*
8	65	*2.54*	48	*1.88*	0	*0.00*	4	*0.16*
9	30	*1.17*	31	*1.21*	0	*0.00*	3	*0.12*
10	12	*0.47*	16	*0.63*	0	*0.00*	1	*0.04*
Total	2555	*100*	2555	*100*	2555	*100*	2555	*100*

A2: Construction of industry categories

The original variable in the GESIS-panel contains the NACE-classification comprising 18 main categories. In order to reduce complexity, we collapsed several industries based on occupational relatedness and cases (representation in the sample). The category merge can is displayed in the following table:

	Industry *(Associated original categories shown in cursive)*	**N**
1	**Construction and Mining**	**119**
	↳ *Construction*	*109*
	↳ *Mining and Quarrying*	*10*
2	**Energy and Water Supply**	**55**
3	**Service Industry**	**498**
	↳ *Financial and Insurance Services*	*92*
	↳ *Professional, Scientific and Technical Services*	*86*
	↳ *Other Personal Services*	*226*
	↳ *Other Business Services*	*55*
	↳ *Real Estate Activities*	*19*
	↳ *Arts, Entertainment and Recreation*	*20*
4	**Upbringing and Education**	**207**
5	**Catering, Lodging, and Gastronomy**	**19**
6	**Health- and Social Care**	**320**
7	**Trade; Maintenance/ Reparation of Motor Vehicles and Consumer Goods**	**115**
8	**Information and Communication**	**120**
9	**Agriculture, Fishery, and Fish Farming**	**32**
10	**Public Administration, Defense, Social Security**	**265**
11	**Processing Industry, Production of Goods**	**288**
12	**Traffic and Storage**	**97**

A3: Regression on DIW, Estimation Comparison (OLS, OLogit, NegBin)

DIW (Digital Involvement at Work)	OLS		OLogit		NegBin	
Sex: Male (Ref.: Female)	**0.407**	***	**0.318**	***	**0.126**	***
	0.114		*0.096*		*0.035*	
Age (in Years)	**-0.017**	***	**-0.014**	***	**-0.005**	***
	0.050		*0.004*		*0.002*	
Education (Ref.: max. General Secondary School)						
Intermediate Secondary School	**0.535**	**	**0.510**	**	**0.204**	*
	0.206		*0.194*		*0.087*	
Higher Secondary School	**0.933**	***	**0.909**	***	**0.343**	***
	0.219		*0.201*		*0.087*	
Occup. Qual.: Vocational Training (Ref.: Tertiary Education)	**-0.675**	***	**-0.572**	***	**-0.204**	***
	0.130		*0.110*		*0.039*	
Weekly Working Hours	**0.040**	***	**0.034**	***	**0.015**	***
	0.007		*0.006*		*0.003*	
Industrial Sector (Ref.: Construction and Mining)						
Energy and Water Supply	**0.853**	*	**0.649**	*	**0.234**	*
	0.392		*0.314*		*0.106*	
Service Industry	**0.505**	*	**0.402**	*	**0.136**	*
	0.217		*0.180*		*0.066*	
Upbringing and Education	**-0.705**	**	**-0.587**	**	**-0.268**	***
	0.234		*0.196*		*0.080*	
Catering, Lodging, and Gastronomy	**-0.313**		**-0.286**		**-0.118**	
	0.435		*0.371*		*0.167*	
Health- and Social Care	**0.180**		**-0.172**		**-0.077**	
	0.232		*0.197*		*0.077*	
Trade; Maintenance/Reparation of Motor Vehicles and Consumer Goods	**0.103**		**0.052**		**0.034**	
	0.300		*0.253*		*0.102*	
Information and Communication	**0.621**	*	**0.519**	*	**0.138**	+
	0.291		*0.247*		*0.080*	
Agriculture, Fishery and Fish Farming	**-0.880**	+	**-0.781**		**-0.315**	+
	0.458		*0.476*		*0.189*	
Public Administration, Defense, Social Security	**0.211**		**0.145**		**0.062**	
	0.240		*0.195*		*0.073*	
Processing Industry, Production of Goods	**0.026**		**-0.003**		**-0.013**	
	0.230		*0.198*		*0.073*	
Traffic and Storage	**0.553**	+	**0.446**		**0.146**	
	0.332		*0.298*		*0.094*	
Technology Affinity (Ref.: No Tech Affinity)						
Low Tech Affinity	**0.421**	**	**0.372**	**	**0.201**	***
	0.139		*0.124*		*0.059*	
Moderate Tech Affinity	**1.012**	***	**0.853**	***	**0.389**	***
	0.143		*0.128*		*0.057*	
High Tech Affinity	**1.366**	***	**1.184**	***	**0.483**	***
	0.151		*0.136*		*0.057*	
Constant	**1.213**	*			**0.307**	+
	0.492				*0.173*	
N	1823		1823		1823	
AIC	7,830.064		7,468.094		7,694.510	
BIC	7,945.737		7,633.341		7,815.691	

DV: DIW index (11 categories: [0;10]); Estimation Results from Regression Analyses, Std.Err. below; Significance: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001
Models: [OLS] Ordinary Least Square Regression, [OLogit] Ordered Logit Regression, [NegBin] Negative Binomial Regression

A4: Hierarchical Negative Binomial Regression on DIW, Full Model

DIW (Dig. Involvement at Work)	**(1) Raw DGD**	**(2) Adj. DGD**	**(3) Adj. DGD**	**(4) Adj. DGD**
Sex: Male (Ref.: Female)	**1.374** *** *0.038*	**1.339** *** *0.038*	**1.165** *** *0.042*	**1.134** *** *0.040*
Age (in Years)		**0.995** *** *0.001*	**0.993** *** *0.002*	**0.995** *** *0.002*
Education (Ref.: max. General Secondary School)				
Intermediate Secondary School		**1.182** * *0.09*	**1.231** * *0.11*	**1.226** * *0.107*
Higher Secondary School		**1.325** *** *0.101*	**1.426** *** *0.129*	**1.410** *** *0.124*
Occup. Qual.: Vocational Training (Ref.: Tertiary Education)		**0.819** *** *0.029*	**0.813** *** *0.033*	**0.815** *** *0.032*
Weekly Working Hours			**1.017** *** *0.003*	**1.015** *** *0.003*
Industrial Sector (Ref.: Construction and Mining)				
Energy and Water Supply			**1.264** * *0.134*	**1.264** * *0.134*
Service Industry			**1.149** * *0.081*	**1.146** * *0.076*
Upbringing and Education			**0.730** *** *0.062*	**0.765** *** *0.061*
Catering, Lodging, and Gastronomy			**0.866** *0.145*	**0.889** *0.149*
Health- and Social Care			**0.906** *0.074*	**0.093** *0.071*
Trade; Maintenance/Reparation of Motor Vehicles and Consumer Goods			**1.016** *0.108*	**1.034** *0.106*
Information and Communication			**1.209** * *0.099*	**1.148** + *0.092*
Agriculture, Fishery and Fish Farming			**0.685** * *0.132*	**0.730** + *0.138*
Public Administration, Defense, Social Security			**1.049** *0.081*	**1.063** *0.077*
Processing Industry, Production of Goods			**0.976** *0.075*	**0.987** *0.072*
Traffic and Storage			**1.175** *0.116*	**1.158** *0.109*
Technology Affinity (Ref.: No)				
Low Tech Affinity				**1.222** *** *0.073*
Moderate Tech Affinity				**1.476** *** *0.084*
High Tech Affinity				**1.620** *** *0.093*
Constant	**1.015** *** *0.022*	**3.206** *** *0.336*	**1.885** *** *0.322*	**1.359** + *0.236*
Alpha	**0.217** *** *0.018*	**0.175** *** *0.017*	**0.148** *** *0.019*	**0.199** *** *0.018*
N	2550	2377	1827	1823
AIC	11,000.000	10,000.000	7,806.321	7,694.510
BIC	11,000.000	10,000.000	7,911.019	7,815.691

DV: DIW index (11 categories: [0;10]); Estimation Results: Incidence Rate Ratios from Negative Binomial Regression, Std.Err. below; Significance: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

A5: Negative Binomial Regressions on Tech Involvement Indices by Domain

Dependent Variable: Tech Involvement Indices		*(1) DIW*		*(2) OWT*		*(3) DIP*		*(4) OPT*	
		IRR	Sig	**IRR**	Sig	**IRR**	Sig	**IRR**	Sig
Raw Gender Effect (without Tech Affinity)	N=2550	**1.374**	***	**1.343**	***	**1.190**	***	**0.916**	*
		0.038		*0.063*		*0.026*		*0.039*	
Gender: male [Ref. female]		**1.305**	***	**1.327**	***	**1.138**	***	**0.923**	+
		0.039		*0.069*		*0.027*		*0.043*	
Technology Affinity [Ref. tech unimportant]									
technology somewhat important/useful		**1.257**	***	**1.168**	+	**1.145**	**	**0.985**	
		0.072		*0.101*		*0.054*		*0.074*	
technology rather important/useful		**1.559**	***	**1.267**	**	**1.363**	***	**0.985**	
		0.084		*0.106*		*0.061*		*0.074*	
technology important/useful		**1.762**	***	**1.249**	*	**1.582**	***	**1.083**	
		0.095		*0.109*		*0.071*		*0.084*	
lnalpha		**0.184**	***	**0.408**	***	**0.003**	+	**0.375**	***
		0.019		*0.048*		*0.009*		*0.040*	
N		2150		2150		2150		2150	

Estimates: Incidence Rate Ratios from Negative Binomial Regressions; Standard Errors below; Significance: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001
Models: [DIW] min at work; [OWT] only at work; [DIP] min in private; [OPT] only in private

A6: Regression on DIW, Ordered Logit, Effect of Technology Interest

DIW (Dig. Involvement Index)	**DGD**		**Men**		**Women**		**Interaction**	
Sex: Female (Ref.: Male)	**0.770**	***					**0.721**	***
	0.023						*0.044*	
Technology Interest (Ref.: No)	**1.442**	***	**1.375**	***	**1.510**	***	**1.375**	***
	0.051		*0.067*		*0.075*		*0.067*	
Interact: Male + No Tech Interest (Ref)								
Interact: Female + Tech Interest							**1.098**	
							0.077	
N	2154		1122		1032		2154	
AIC	9,329.159		5,067.582		4,255.100		9,329.286	
BIC	9,351.860		5,082.651		4,269.918		9,357.661	

DV: DIW index (11 categories: [0;10]); Estimation Results: Incidence Rate Ratios from Negative Binomial Regression Analysis, Std.Err. below; Significance: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

A7: Ordered Logit Regression on Personal Income (GPG), Full Model

Personal Net Income	(1) Raw GPG		(2) Adj. GPG		(3) Adj. GPG		(4) Adj. GPG	
Sex: Male (Ref.: Female)	**4.804**	***	**5.102**	***	**2.810**	***	**2.631**	***
	0.371		*0.422*		*0.292*		*0.281*	
Age (in Years)			**1.018**	***	**1.017**	***	**1.023**	***
			0.004		*0.004*		*0.005*	
Education (Ref.: General Second. School)								
Intermediate Secondary School			**1.681**	***	**1.274**		**1.127**	
			0.247		*0.229*		*0.191*	
Higher Secondary School			**3.156**	***	**2.919**	***	**2.445**	***
			0.495		*0.560*		*0.448*	
Occup. Qual.: Vocational Training (Ref.: Tertiary Education)			**0.330**	***	**0.325**	***	**0.363**	***
			0.031		*0.035*		*0.040*	
Weekly Working Hours					**1.154**	***	**1.150**	***
					0.011		*0.011*	
Industrial Sector (Ref.: Construction & Mining)								
Energy and Water Supply					**2.029**	*	**1.701**	+
					0.629		*0.510*	
Service Industry					**1.381**		**1.213**	
					0.293		*0.260*	
Upbringing and Education					**1.805**	*	**2.280**	***
					0.430		*0.559*	
Catering, Lodging, and Gastronomy					**0.395**	*	**0.446**	*
					0.154		*0.165*	
Health- and Social Care					**1.580**	*	**1.756**	*
					0.351		*0.399*	
Trade; Maintenance/Reparation of Motor Vehicles and Consumer Goods					**0.540**	*	**0.529**	*
					0.151		*0.150*	
Information and Communication					**1.520**		**1.276**	
					0.422		*0.372*	
Agriculture, Fishery and Fish Farming					**0.383**	+	**0.488**	
					0.189		*0.228*	
Public Administration, Defense, Social Security					**2.078**	***	**2.019**	**
					0.444		*0.440*	
Processing Industry, Production of Goods					**1.820**	**	**1.843**	**
					0.402		*0.408*	
Traffic and Storage					**1.136**		**0.966**	
					0.317		*0.266*	
DIW (Digital Involvement at Work Index)							**1.244**	***
							0.026	
Technology Affinity (Ref.: No)								
Low Tech Affinity							**1.162**	
							0.160	
Moderate Tech Affinity							**1.327**	*
							0.179	
High Tech Affinity							**1.435**	*
							0.202	

cut								
cut 1	**0.007**	***	**0.018**	***	**0.556**		**1.204**	
	0.002		*0.007*		*0.362*		*0.794*	
cut 2	**0.049**	***	**0.116**	***	**5.178**	***	**11.355**	***
	0.006		*0.033*		*2.580*		*5.846*	
cut 3	**0.313**	***	**0.782**		**65.056**	***	**146.746**	***
	0.020		*0.201*		*32.040*		*74.795*	
cut 4	**0.849**	**	**2.428**	***	**296.953**	***	**716.974**	***
	0.048		*0.622*		*150.503*		*378.117*	
cut5	**2596.000**	***	**8754.000**	***	**1476.304**	***	**3906.751**	***
	0.158		*2.286*		*772.510*		*2135.796*	
cut 6	**5.517**	***	**20.896**	***	**4000.822**	****	**11000.000**	***
	0.369		*5.546*		*2126.476*		*6180.124*	
cut 7	**13.948**	***	**60.896**	***	**13000.000**	***	**39000.000**	***
	1.088		*16.654*		*7236.791*		*22000*	
cut 8	**32.212**	***	**147.690**	***	**36000.000**	***	**110000.000**	***
	3.027		*41.083*		*20000.000*		*62000.000*	
N	**2430**		**2274**		**1758**		**1744**	
AIC	9,177.138		8,147.644		5,786.285		5,617.351	
BIC	9,229.299		8,222.125		5,923.084		5,775.805	

DV: Personal Net Income (9 categories); Estimates: Odds Ratios from Ordered Logit Regressions, Std.Err. below; Significance: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001