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THE LABOR MARKET IMPACT OF DIGITAL TECHNOLOGIES

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ABSTRACT

We investigate the impact of digital technology on employment patterns in Korea, where firms have rapidly adopted digital technologies such as artificial intelligence (AI), big data, and the internet of things (IoT). By exploiting regional variations in technology exposure, we find significant negative effects on high-skill and female workers, particularly those in non-IT (information technology) services. This contrasts with previous technological disruptions, such as the IT revolution and robotization, which primarily affected low-skill male workers in manufacturing. In IT services, although high-skill employment declined, vacancy postings for high-skill workers increased, implying a shift in labor demand toward newer skill sets. These findings highlight both the labor displacement and the new opportunities generated by digital transformation.

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1 Introduction

Technological advancements and their effects on labor markets have been a central focus of research for decades. Recently, the rise of generative artificial intelligence (AI) has sparked even greater interest in how new technologies will reshape employment patterns. While it is well established that the IT (information technology) revolution contributed to job polarization by replacing routine tasks (e.g. Autor et al., 2003; Autor and Dorn, 2013; Lee and Shin, 2017; Aum et al., 2018), there is a growing need for empirical research to understand the effects of newer digital technologies, such as AI, big data analytics, and the Internet of Things (IoT). These digital technologies are anticipated to transform production processes and work practices, with some suggesting that their impacts could differ significantly from those seen during the IT revolution (e.g. Bharadwaj et al., 2013; Adner et al., 2019). In particular, the potential of digital technologies to alter the demand for workers with different skill sets has become a crucial subject of investigation.

We examine how digital technology has influenced employment patterns in Korea, a country at the forefront of digital transformation. By leveraging regional variations in exposure to digital technology, we analyze the employment effects of AI, big data, and IoT across workers in different occupations and sectors, categorized by gender and education level. We find that the adoption of digital technologies may lead to outcomes distinct from those of previous technological shifts, such as the IT revolution or advances in industrial robotics.

The adoption of digital technologies in Korea appears to have a more pronounced negative impact on high-skill and female workers. This suggests that the nature of labor displacement caused by AI, big data, and IoT may differ from that of previous technological disruptions, which primarily affected male and low-skill workers.

Across industries, the negative effects of digital technology adoption on employment have been largest in non-IT services rather than in manufacturing. However, within each industry, the effect varied across occupations. In manufacturing, craft workers were the most affected, mirroring the pattern of job polarization caused by automation and robotization. In contrast, in IT services, professionals experienced the greatest employment reductions. In the broader services sector outside IT, elementary occupations—which have historically been less vulnerable to IT disruption—saw the steepest employment declines. These findings by occupation and industry underscore the complexity of digital technology's impact on labor markets.

Furthermore, the relationship between employment declines and job vacancies differed significantly across sectors and occupations. In manufacturing, craft jobs experienced reductions in both employment and vacancies, indicating diminished demand. In contrast, professional roles in IT services exhibited a paradoxical trend: while employment fell, vacancy postings for these positions increased, signaling a growing demand for professionals with new skill sets adapted to the new digital technologies. While digital technologies may reduce the number of traditional jobs, they are also creating new opportunities for workers who can meet the demands of evolving roles.

Related Literature The relationship between technological change and labor market dynamics has long been a subject of interest among the general public, academics, and policymakers. Numerous studies have sought to understand the effects of specific technological waves, starting with the IT revolution and extending to more recent innovations in robotics and AI.

Autor et al. (2003), Autor and Dorn (2013), and Aum et al. (2018) highlight the role of IT in contributing to job polarization by displacing routine jobs and increasing demand for high-skill workers.[1] More recent studies, such as Graetz and Michaels (2018), Acemoglu and Restrepo (2020), and Dauth et al. (2021), have investigated the impact of robots, presenting a nuanced picture where robots substitute manual labor while complementing higher-skill tasks. Kim (2024) explored the effects of robot adoption, finding significant declines in routine jobs within the manufacturing sector but minimal impact on service sector employment. Our study extends this analysis to AI, big data, and IoT, revealing that these technologies, unlike IT and robots, have had a more substantial negative impact on high-skill and female employment, especially in non-IT services, rather than primarily affecting low-skill and male workers.

Recently, there has been significant interests in the impact of AI. Webb (2020) suggests that AI exposure is higher in high-skill occupations compared to the exposure

[1] Aum (2020), Aum and Shin (2020) and Aum and Shin (2024) analyze the impact of non-AI software.

to traditional technologies. Babina et al. (2023) found that firms with higher AI investment tend to have more high-skill workers. Acemoglu et al. (2022) analyzed that firms exposed to AI reduce employment in non-AI positions while increasing vacancies for AI-related positions. Eisfeldt et al. (2023) examined the effects of generative AI, raising the possibility that AI may substitute high-skill workers. Abis and Veldkamp (2024) shows that big data and the changing knowledge production will reduce the labor income share in the investment management industry. Our study complements these studies by investigating the impact of AI, big data, and IoT exposure on labor markets in Korea.

Some studies utilize job vacancies as more direct measures of the impact on labor demand. For example, Acemoglu et al. (2022) demonstrated that technological change can lead to a reduction in certain types of jobs while simultaneously creating additional vacancies in others. Kim (2024) found that robotization decreased vacancies for routine jobs in manufacturing. Our findings contribute to this literature by revealing a more complex relationship between digital technologies and job vacancies.

2 Empirical Analysis

2.1 Data

The data used in this analysis come from several national sources that provide comprehensive information on labor market outcomes and digital technology adoption in Korea. The primary data source for employment is the Regional Employment Survey, conducted by Statistics Korea. This survey provides detailed information on regional employment rates, wage levels, and demographic characteristics of workers, including gender, age, and educational attainment. It covers a broad range of industries, allowing for granular analysis at the regional level.

To measure digital technology adoption, we rely on the Survey of Business Activities, which covers all corporate entities with at least 50 regular employees and capital of 300 million KRW (approximately 200,000 USD as of February 2025) or more. This survey reports the extent to which firms across various industries have been adopting digital technologies, including AI, big data, and IoT, since 2017.[2] We utilize data from 2017 to 2019, to avoid potential disruptions caused by the Covid-19 pandemic. Although Korea managed to contain the pandemic better than most other countries, even without a lockdown, we aim to ensure our analysis is not influenced by any pandemic-related anomalies (Aum et al., 2021).[3] Using the survey, we calculate regional exposure to digital technologies by weighting industry-level adoption rates by the employment share of each industry within a given region, because the adoption by industry is only available at the national level.

We also use data from the Survey on the Supply and Demand of Industrial Technicians. This survey covers a range of occupations across various industries, including manufacturing, information and communications technology, professional scientific and technical services, business support services, education services, and health and social welfare services. It focuses on industrial technicians and provides information on current employment and vacancies for each occupation within each industry.

2.2 Specification

To assess the impact of digital technologies—AI, big data, and IoT—on employment and job vacancies across industries and regions in Korea, we adopt an empirical framework similar to those used in previous studies on the impact of technological change. The specification follows a standard approach that links regional labor market outcomes to the exposure of local industries to digital technologies, akin to the methodology as employed in Acemoglu and Restrepo (2020) for robots.

[2] The survey defines digital technologies as innovations integrating the physical, biological, and digital domains through big data, with the potential to impact the economy. Big data is defined as "large-scale data generated in digital environments, characterized by vast volume, rapid generation cycles, and diverse formats, including numeric, textual, and visual data." Artificial intelligence is defined as "technology that implements human abilities such as learning, reasoning, perception, and natural language understanding through computer programs."

[3] By focusing on the 2017–2019 period, our analysis examines relatively short-term impacts. Assessing long-term effects will require a longer time series, which could be explored in future research as more data becomes available.

Our baseline specification is:

$$\Delta y_{r,t} = \beta \times DT_{r,t} + X'_{r,t}\gamma + \alpha_r + \delta_t + \epsilon_{r,t} \;, \tag{1}$$

where $\Delta y_{r,t}$ represents the change in employment or vacancy rates of region r; $X_{r,t}$ includes control variables such as the region's demographic composition (e.g., gender, age, and education) and industry structure; and the key explanatory variable, $DT_{r,t}$, measures the degree of digital technology adoption in region r in time t. We include region fixed effects (α_r) and year fixed effects (δ_t) to account for unobserved heterogeneity across regions and periods. We use the population of each region as weights in the regression analysis.

Digital technology exposure ($DT_{r,t}$) is constructed by weighting the industry-specific technology adoption rate at the national level by the employment share of each industry within the region. This approach allows us to capture the differential impact of technology adoption across regions based on their industrial composition. Specifically:

$$DT_{r,t} = \sum_n \lambda_{r,0,n} \Delta T_{n,t} \tag{2}$$

where $\lambda_{r,0,n}$ is the employment share of industry n in region r in the baseline year (2016), and $T_{n,t}$ represents the adoption rate of digital technologies in industry n at year t at the national level. This specification allows us to evaluate how regions with different industrial compositions are exposed to digital technologies and how this exposure influences employment and vacancies at the region level.

The explanatory variable in our regression combines initial exposure with changes over time and can be regarded as a shift-share instrument. Unless certain regions adopted digital technologies more actively for reasons unrelated to nationwide industry-level diffusion, the regression estimates may represent a causal relationship. Acemoglu and Restrepo (2020), for instance, further instrumented a similar shift-share variable with international counterparts. However, due to data limitations, we did not pursue additional instrumental variables in this analysis.

Our focus on regional variation in technology exposure is similar to that of Acemoglu and Restrepo (2020) and Kim (2024), who analyzed the impact of robots in the US and Korea, respectively. By leveraging regional differences in industry structure and, consequently, technology adoption, we aim to analyze how digital technologies affect labor markets across sectors and occupations.

3 Estimation Results

Our estimation results provide unique insights into how digital technologies, such as AI, big data, and IoT, reshape labor market dynamics across various industries and occupations. By examining employment and vacancy patterns, we observe notable variations in how these technologies influence different sectors and demographic groups. In this section, we report the estimated effects categorized by industry, gender, education, and occupation.

3.1 Overall Effect

Table 1 shows the employment effects of AI, big data, and IoT across all industries. We find a consistent negative impact of these technologies on total employment, with all effects being statistically significant. This negative effects mirror previous findings in the literature, such as those by Acemoglu and Restrepo (2020), which showed a similar reduction in employment due to the adoption of robots.

By Gender The analysis shows a gender disparity in the effects of digital technologies. Female employment experiences a stronger negative impact than male employment, particularly with AI. This contrasts with the previous IT revolution, which primarily reduced male employment.

By Education The results by educational attainment show an interesting contrast between workers with higher education (some college or more) and those with less education. More educated workers have experienced significant declines in employment with increased digital technology adoption, while workers with less education have seen an increase in employment. This result challenges the conventional view that higher education protects workers from technological displacement. Our findings indicate that, when it comes to digital technologies, even high-skill workers are

Table 1: Impact of Digital Technology on Employment, All Industries

	AI		Big Data		IoT	
Total Employment	-0.197^{*}	(0.115)	-0.159^{***}	(0.050)	-0.074^{*}	(0.041)
By gender						
Male	-0.075	(0.083)	-0.071^{**}	(0.036)	-0.034	(0.027)
Female	-0.121^{***}	(0.046)	-0.089^{***}	(0.026)	-0.040^{*}	(0.022)
By age						
Young	-0.161^{*}	(0.091)	0.010	(0.075)	0.021	(0.057)
Old	0.032	(0.086)	-0.099^{*}	(0.058)	-0.049	(0.043)
By education						
$\geq$ Some college	-2.025^{***}	(0.512)	-2.324^{***}	(0.470)	-1.554^{***}	(0.367)
$\leq$ High school	1.828^{***}	(0.505)	2.165^{***}	(0.474)	1.480^{***}	(0.364)

Note: The dependent variable is the change in the employment-to-population ratio (%) at the regional (si-gun-gu) level, and the regression is weighted by population. Standard errors clustered at the regional level are in parentheses. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% levels, respectively. For age groups, "young" refers to individuals who are 25 years or older but less than 50 years old, and "old" refers to individuals who are 50 years or older.

at risk of displacement. This new result is crucial for understanding the broader effects of digital transformation on labor markets.

3.2 Effect across Industries

Table 2 breaks down the impact of digital technology adoption on employment across three major industries: manufacturing, IT services, and non-IT services. The effects of digital technologies on employment vary significantly across these industries, highlighting the diverse ways in which these technologies reshape labor demand.

Manufacturing In the manufacturing sector, AI and IoT show statistically insignificant effects. In contrast, the estimate for big data shows a statistically significant negative impact (-0.039), indicating that it is driving some displacement. While the estimate for big data aligns with findings from previous studies on automation technologies, such as robots, to which manufacturing has historically been more susceptible (Acemoglu and Restrepo, 2020), the overall effect of digital technologies remains modest.

IT Services In the IT services industry, we find that big data and IoT have a positive and statistically significant effect on total employment, implying reallocation across industries. Big data (0.049) and IoT (0.040) both increase employment, especially among male workers. This aligns with findings from studies such as Dauth et al. (2021), which noted that displacement effects in manufacturing are offset by new jobs in services. These positive effects suggest that the IT services industry is well-positioned to leverage digital technologies for employment growth, particularly in low-skill roles.

Non-IT Services In the non-IT services sector, by contrast, we find a strong negative impact of digital technology adoption on employment. AI (-0.223), big data (-0.150), and IoT (-0.102) all have significant negative effects. This finding suggests that the adoption of digital technologies in non-IT services sectors leads to considerable displacement, particularly affecting female workers and high-skill workers.

Table 2: Impact of Digital Technology on Employment, By Industry

	AI		Big Data		IoT	
Manufacturing						
Total Employment	0.010	(0.040)	−0.039*	(0.023)	−0.017	(0.017)
By gender						
Male	0.018	(0.047)	−0.021	(0.028)	−0.010	(0.022)
Female	−0.007	(0.033)	−0.018	(0.022)	−0.006	(0.015)
By education						
≥ Some college	−1.008***	(0.237)	−0.202	(0.214)	−0.142	(0.192)
≤ High school	1.018***	(0.259)	0.163	(0.220)	0.125	(0.199)
	AI		Big Data		IoT	
IT Services						
Total Employment	0.026	(0.027)	0.049*	(0.025)	0.040**	(0.019)
By gender						
Male	0.014	(0.019)	0.032**	(0.015)	0.025**	(0.011)
Female	0.012	(0.016)	0.018	(0.016)	0.014	(0.012)
By education						
≥ Some College	−0.239	(0.160)	−0.403**	(0.160)	−0.290**	(0.119)
≤ Highschool	0.265	(0.171)	0.452**	(0.179)	0.330**	(0.133)
	AI		Big Data		IoT	
Non-IT Services						
Total Employment	−0.223**	(0.091)	−0.150**	(0.059)	−0.102**	(0.042)
By gender						
Male	−0.065	(0.064)	−0.036	(0.037)	−0.031	(0.027)
Female	−0.158***	(0.057)	−0.114***	(0.039)	−0.071***	(0.027)
By education						
≥ Some college	−0.718	(0.522)	−1.618***	(0.499)	−1.069***	(0.382)
≤ High school	0.495	(0.499)	1.468***	(0.474)	0.967***	(0.364)

Note: The dependent variable is the change in the employment-to-population ratio (%) at the regional (si-gun-gu) level, and the regression is weighted by population. Standard errors clustered at the regional level are in shown parentheses. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% levels, respectively.

3.3 Effect across Occupations

Table 3 reports the effects of AI, big data, and IoT adoption on employment across occupations in manufacturing, IT services, and non-IT services. The results indicate that the impact of digital technology on employment is highly heterogeneous, varying significantly by occupation and industry.

Manufacturing In the manufacturing sector, the effects are concentrated on specific occupational groups. Notably, clerical support roles experience significant positive employment effects with respect to big data (0.383), whereas craft and related trades face significant declines in employment due to big data (-0.380). This aligns with the literature that identifies routine and manual jobs as more vulnerable to technological displacement, similar to the effects of robot adoption (Acemoglu and Restrepo, 2020; Dauth et al., 2021). On the other hand, machine operators and assemblers show no statistically significant impact from AI or IoT, suggesting that digital technologies in manufacturing may not yet have fully displaced manual labor beyond specific craft jobs.

IT Services In IT services, the most pronounced effect is observed in professional and technical occupations, where employment decreases significantly with the adoption of all three technologies: AI (-2.629), big data (-1.586), and IoT (-0.868). This stands in contrast to previous findings from the IT revolution, where high-skill occupations typically benefited from technological advancements (Autor and Dorn, 2013; Aum, 2020). These results indicate that digital technologies, particularly AI and big data, are reshaping the demand for professionals, potentially necessitating new skill sets, as suggested by recent literature on the effects of AI adoption (Acemoglu et al., 2022; Eisfeldt et al., 2023).

Non-IT Services In the non-IT services industry, elementary occupations experience sharp declines in employment with due to AI (-0.207), big data (-0.263), and IoT (-0.190). These findings are consistent with broader trends identified in non-IT service industries, where routine and manual jobs have been more vulnerable to displacement by technological change.

Table 3: Impact of Digital Technology on Employment, By Occupation

	AI		Big Data		IoT	
Manufacturing						
Managers	0.000	(0.053)	0.072	(0.050)	0.033	(0.029)
Professionals and Technicians	−0.196	(0.134)	0.104	(0.142)	0.096	(0.111)
Clerical Support	0.255	(0.188)	0.383**	(0.190)	0.192	(0.111)
Services	−0.004	(0.026)	−0.024	(0.025)	−0.012	(0.015)
Sales	0.059	(0.058)	0.012	(0.048)	0.019	(0.029)
Craft and Related Trades	0.078	(0.192)	−0.380**	(0.189)	−0.212	(0.127)
Machine Operators and Assemblers	−0.133	(0.180)	−0.071	(0.176)	−0.046	(0.103)
Elementary	−0.061	(0.124)	−0.096	(0.111)	−0.069	(0.066)

	AI		Big Data		IoT	
IT Services						
Managers	0.199	(0.348)	0.204	(0.265)	0.073	(0.156)
Professionals and Technicians	−2.629***	(0.940)	−1.586**	(0.639)	−0.868**	(0.438)
Clerical Support	1.309	(1.013)	0.847	(0.671)	0.629	(0.433)
Services	−0.003	(0.183)	0.077	(0.104)	0.079	(0.074)
Sales	0.345	(0.524)	0.444	(0.305)	0.307	(0.192)
Craft and Related Trades	0.216	(0.491)	0.258	(0.383)	0.066	(0.246)
Machine Operators and Assemblers	0.140	(0.238)	0.102	(0.131)	0.024	(0.095)
Elementary	0.422	(0.654)	−0.344	(0.468)	−0.309	(0.328)

	AI		Big Data		IoT	
Non-IT Services						
Managers	0.029	(0.033)	0.018	(0.026)	0.011	(0.019)
Professionals and Technicians	−0.093	(0.182)	0.081	(0.107)	0.068	(0.082)
Clerical Support	0.025	(0.118)	0.188**	(0.090)	0.104*	(0.059)
Services	0.023	(0.107)	−0.048	(0.078)	−0.027	(0.057)
Sales	−0.008	(0.118)	0.010	(0.078)	0.016	(0.056)
Craft and Related Trades	0.089	(0.072)	0.002	(0.044)	−0.004	(0.031)
Machine Operators and Assemblers	0.412*	(0.076)	0.012	(0.042)	0.024	(0.029)
Elementary	−0.207*	(0.109)	−0.263***	(0.080)	−0.190***	(0.055)

Note: The dependent variable is the change in the employment-to-population ratio (%) at the regional (si-gun-gu) level, and the regression is weighted by population. Standard errors clustered at the regional level are shown in parentheses. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% levels, respectively.

Discussion Our analysis does not directly test the mechanisms driving the observed employment declines. Theoretically, employment in jobs highly exposed to a particular technology is expected to decline when the substitutability between the technology and labor within a given task exceeds the substitutability between tasks performed by workers (Lee and Shin, 2017; Acemoglu and Restrepo, 2020). Given the nature of digital technology, this pattern is particularly relevant for occupations with task structures that are cognitive in nature yet relatively straightforward to digitalize (Webb, 2020; Eisfeldt et al., 2023).

For example, clinical laboratory technologists and technicians may see reduced demand as AI tools enhance the efficiency and accuracy of diagnostic tasks, potentially minimizing the need for human judgment in routine testing procedures. Similarly, proofreaders and translators face challenges as natural language processing technologies improve, enabling software to handle textual review tasks that were once the domain of human expertise.[4] While our findings do not pinpoint specific mechanisms, these examples illustrate how digital transformation could reshape employment in roles characterized by such task profiles.

3.4 Vacancies

Table 4 presents how digital technology adoption affects vacancy postings across different industries and occupations, and by educational attainment. The results provide a nuanced picture of how AI, big data, and IoT influence labor demand for new positions in both the manufacturing and services sectors.

Manufacturing In the manufacturing sector, the impact of digital technologies on total vacancies is insignificant. This relatively smaller impact indicates that, while digital technologies are reshaping employment, they are not yet driving a significant increase in new job opportunities in manufacturing.

[4] Clinical laboratory technologists and proofreaders rank in the 80th percentile or higher for Webb (2020)'s AI exposure index and female employment share, with above-median fraction of college-educated workers. Similar occupations include data entry keyers, occupational therapists, psychologists, registered nurses, veterinarians, and audiologists.

Table 4: Impact of Digital Technology on Vacancies

	AI		Big Data		IoT	
Manufacturing						
Total Vacancies	0.211	(0.277)	0.273	(0.168)	0.114	(0.104)
By Education						
Bachaelor	0.071	(0.120)	0.103	(0.069)	0.055	(0.043)
Master	−0.009	(0.035)	0.032	(0.028)	0.013	(0.015)
Doctorate	−0.001	(0.004)	−0.001	(0.002)	0.000	(0.001)
By Occupation						
ICT Professionals	−0.111	(0.079)	−0.203*	(0.027)	−0.025	(0.021)
Metal, Machinery Related Trades	−0.016	(0.013)	−0.021	(0.012)	−0.011	(0.008)
Electronic Related Trades	0.001	(0.009)	−0.022***	(0.003)	−0.007	(0.005)
	AI		Big Data		IoT	
IT Services						
Total Vacancies	0.135	(0.139)	0.188*	(0.104)	0.155***	(0.050)
By Education						
Bachaelor	0.174	(0.130)	0.189*	(0.103)	0.143***	(0.050)
Master	−0.023	(0.018)	−0.006	(0.008)	0.001	(0.005)
Doctorate	−0.001	(0.003)	0.000	(0.002)	0.001	(0.001)
By Occupation						
ICT Professionals	0.220**	(0.094)	0.320***	(0.070)	0.161**	(0.069)
	AI		Big Data		IoT	
Non-IT Services						
Total Vacancies	−0.069	(0.087)	0.021	(0.066)	0.009	(0.045)
By Education						
Bachaelor	−0.090	(0.080)	−0.017	(0.056)	−0.005	(0.039)
Master	0.000	(0.017)	0.014	(0.015)	0.004	(0.008)
Doctorate	0.012	(0.009)	0.012**	(0.006)	0.004	(0.003)
By Occupation						
ICT Professionals	0.014	(0.027)	0.013	(0.018)	0.014	(0.011)

Note: The dependent variable is the change in the vacancies-to-population ratio (%) at the regional (si-do) level, and the regression is weighted by population. Standard errors clustered at the regional level are shown in parentheses. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% levels, respectively.

IT Services In the IT services industry, the adoption of digital technologies, particularly big data (0.188) and IoT (0.155), is positively associated with vacancy postings, indicating a growing demand for workers with technical skills. These findings align with Acemoglu et al. (2022), which showed that digital transformation creates high-skill job opportunities, especially in AI-related fields. The impact is particularly pronounced for ICT professionals, contrasting with other sectors where the demand for new skills is more subdued.

Non-IT Services In the non-IT services industry, digital technologies appear to have a more neutral effect on vacancy postings. This suggests that the adoption of digital technologies in non-IT services does not yet create significant labor demand. One exception is the effect of big data, which positively impacts vacancy postings for individuals with doctorate degrees.

4 Conclusion

This paper has examined the impact of new digital technologies—AI, big data, and IoT—on labor markets in Korea, focusing on their effects across different industries, occupations, and demographic groups. Our analysis reveals several key findings. First, digital technology adoption has had a significant negative impact on high-skill and female workers, marking a departure from earlier technological changes, such as the IT revolution and robot adoption, which primarily affected male and low-skill workers. Second, the effects of digital technologies vary by industry, with the most pronounced negative impacts observed in the non-IT services industry. The occupations most affected differ across industries: Craft jobs in manufacturing, professionals in IT services, and elementary occupations in other services have all experienced significant declines.

Moreover, the analysis of job vacancies shows an interesting dynamic. While digital technologies reduce employment in certain sectors, they simultaneously increase demand for workers with new skill sets. This is particularly evident in IT services, where vacancies for professionals have increased even as their employment declined. This suggests that digital transformation is not merely eliminating jobs but also reshaping labor demand, creating opportunities for those who can adapt to new technologies.

The findings of this study have important implications. As digital technologies continue to evolve, labor markets will require substantial adjustments, particularly in terms of retraining and up-skilling workers to meet new demands. Policymakers and firms should focus on supporting education and training programs that can equip workers with the skills necessary to thrive in a digitally-driven economy.

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