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 cloud computing. By exploiting regional variations in technology exposure, we find significant negative effects on 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 male workers in manufacturing. The negative employment effect of AI did not differ across educational groups, but big data and cloud computing more negatively affected workers with less education. In IT services, although employment shares of professionals and technicians declined, vacancy postings for these positions increased, implying a shift in labor demand toward newer skill sets within the same occupations. These findings highlight both the labor displacement and the new opportunities generated by digital transformation.

JEL codes: E24, J21, J23, O33

Federal Reserve Bank of St. Louis *Review*, Second Quarter 2025, Vol. 107, No. 5, pp. 1-10.
https://doi.org/10.20955/r.2025.05

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 (Autor, Levy, and Murnane, 2003; Autor and Dorn, 2013; Lee and Shin, 2017; Aum, Lee, and Shin, 2018), there is a growing need for empirical research to understand the effects of newer digital technologies, such as AI, big data analytics, and cloud computing. 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 (Bharadwaj et al., 2013; Adner, Puranam, and Zhu, 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

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the employment effects of AI, big data, and cloud computing 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 negative effect on employment. The negative effect is more pronounced for female workers. By educational groups, while AI does not show a significantly different effect, big data and cloud computing more negatively affect the employment of less educated workers.

Across industries, the negative effects of digital technology adoption on employment have been largest in non-IT services rather than in manufacturing. Women were especially negatively affected in non-IT services. Employment in IT services, on the other hand, was positively affected by big data and cloud computing, implying reallocation across sectors. The employment of men and less educated workers within IT services rose in response to the adoption of big data and cloud computing. Within each industry, the effect varied across occupations. In manufacturing, craft workers were the most negatively affected by big data and cloud computing, mirroring the pattern of job polarization caused by automation and robotization. In contrast, in IT services, professionals and technicians experienced the greatest reductions in employment shares. In non-IT services, elementary occupations—which have historically been less vulnerable to IT disruption—saw the steepest declines in employment shares. These findings by occupation and industry underscore the complexity of digital technology's impact on labor markets.

The pronounced negative effect on female workers in non-IT services suggests that the nature of labor displacement caused by AI, big data, and cloud computing may differ from that of previous technological disruptions, which primarily affected male workers in manufacturing.

Finally, we find that the relationship between employment declines and job vacancies differed significantly across sectors and occupations. In manufacturing, craft jobs experienced reductions in both employment shares and vacancies, indicating diminished demand. In contrast, professional roles in IT services exhibited a paradoxical trend: While employment shares 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, Levy, and Murnane (2003), Autor and Dorn (2013), and Aum, Lee, and Shin (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 cloud computing, revealing that these technologies have had a more substantial negative impact on female workers, especially in non-IT services, rather than primarily affecting male workers in manufacturing.[2]

Recently, there has been significant interest in the impact of AI. Webb (2020) suggested that AI exposure is higher in high-skill occupations compared with the exposure 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, Schubert, and Zhang (2023) examined the effects of generative AI, raising the possibility that AI may substitute high-skill workers. Abis and Veldkamp (2024) showed that big data and the changing knowledge production will reduce the labor income share in the investment management industry. Hampole et al. (2025) found that, while occupations highly exposed to AI experienced lower demand compared with less exposed ones, the increase in firm productivity ultimately boosted overall employment across all occupations. Using data from European countries, Albanesi et al. (2025) showed that, on average, women's employment

1. Aum (2020), Aum and Shin (2020), and Aum and Shin (2024) analyze the impact of software, including both non-AI and AI varieties.
2. Prytkova et al. (2024) emphasize that the employment effects of digital technologies depend on the specific type of digital technology considered, using data from Europe.

increased in occupations more exposed to AI. Our study complements these findings by investigating the impact of AI, big data, and cloud computing exposure on labor markets in Korea, across different demographic groups, industries and occupations.

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 paper contributes to this literature by documenting 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 cloud computing, since 2017.[3] For each technology, the survey first asks whether firms are developing it and how (in-house development, domestic outsourcing, or international outsourcing). Next, the survey asks, again for each technology, whether firms are using it and, if so, what the main area of application is (product/service development, production process, sales purposes, marketing strategy, or organizational management). If a firm answers yes to these questions, we determine that the firm has adopted the given digital technology.

We use 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, Lee, and Shin, 2021).[4] 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.

The adoption of digital technologies rose rapidly between 2017 and 2019. In 2017, 4.6 percent of firms reported adopting at least one of AI, big data, or cloud computing. This share increased to 8.9 percent by 2019. Adoption rates varied widely across industries, ranging from 0 percent in mining to 17 percent in finance and 29 percent in IT services. Large firms led this trend. When weighted by firms' employment, which is the appropriate weighting for our analysis, the adoption rate rose from 14.5 percent in 2017 to 29.3 percent in 2019.[5]

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 (ICT), 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 cloud computing—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.

3. 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." Cloud computing is defined as "the provision of large-scale computing resources from data centers via networks, enabling the development of applications and services."

4. 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 become available.

5. When weighted by revenue, the adoption rates were 20.3 percent in 2017 and 42.1 percent in 2019.

Our baseline specification is:

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

where $y_{r,t}$ represents the employment or vacancy rates of region r in time t; $X_{r,t}$ 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:

$$DT_{r,t} = \sum_n \lambda_{r,n,0} \left(T_{n,t} - T_{n,0}\right), \tag{2}$$

where $\lambda_{r,n,0}$ is the employment share of industry n in region r in the baseline year $t = 0$ (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 U.S. 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 cloud computing, 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 cloud computing across all industries. We find a consistent negative impact of these technologies on total employment, with all effects being statistically significant. These 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 Age We do not observe a clear pattern by age when grouping workers into young (ages 25-49) and old (ages 50 and older). AI has a marginally significant negative effect on young workers, while big data has a small negative effect on old workers.

By Education We group workers by educational attainment into those with more education (some college or more) and those with less education (high school or less). The effect of AI on employment does not differ significantly between these two educational groups. This challenges the conventional view that higher education protects workers from technological displacement. On the other hand, big data and cloud computing do

Table 1
Impact of Digital Technology on Employment, All Industries

	AI		Big data		Cloud	
Total employment	–0.197*	(0.114)	–0.159***	(0.050)	–0.074*	(0.041)
By gender						
Male	–0.075	(0.083)	–0.071**	(0.035)	–0.034	(0.027)
Female	–0.121***	(0.046)	–0.089***	(0.026)	–0.040*	(0.022)
By age						
Young	–0.161*	(0.090)	0.010	(0.075)	0.021	(0.056)
Old	0.032	(0.086)	–0.099*	(0.058)	–0.049	(0.042)
By education						
≥ Some college	0.021	(0.111)	0.115	(0.072)	0.097*	(0.053)
≤ High school	–0.217	(0.142)	–0.274***	(0.066)	–0.172***	(0.053)

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 25 years or older but less than 50 years old and "old" refers to individuals 50 years or older.

have strong negative effects on the employment of less educated workers. Cloud computing has a marginally significant positive effect on the employment of more educated workers. These findings are more in line with the effects of earlier rounds of technological changes. As we show in the next section, these patterns differ by industry.

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 cloud computing show no effect on employment. The estimate for big data shows a marginally 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 negligible in manufacturing. The differential impact of big data and cloud computing on more educated (positive) and less educated workers (negative) is strongest in the manufacturing sector. AI has no significant effect on either educational group.[6]

IT Services In the IT services industry, we find that big data and cloud computing have a positive effect on total employment, implying reallocation across industries. This relates to findings from studies such as Dauth et al. (2021), which noted that displacement effects in manufacturing are offset by new jobs in services. The effect is larger for male workers and for those with less education. AI has no discernible effect on employment in IT services.

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 cloud computing (–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 less educated workers.

3.3 Effect across Occupations

Table 3 reports the effects of AI, big data, and cloud computing adoption on employment shares across occupations within 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.

6. By contrast, De Souza (2025) finds that AI negatively impacts the employment of more educated workers but positively affects the employment of less educated workers in the manufacturing sector in Brazil.

Table 2
Impact of Digital Technology on Employment, By Industry

	AI		Big data		Cloud	
Manufacturing						
Total employment	0.010	(0.040)	−0.039*	(0.023)	−0.017	(0.017)
By gender						
Male	0.018	(0.046)	−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	0.047	(0.034)	0.046**	(0.022)	0.043**	(0.018)
≤ High school	−0.037	(0.050)	−0.084***	(0.029)	−0.059**	(0.025)
	AI		Big data		Cloud	
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	0.020	(0.024)	0.031	(0.025)	0.026	(0.018)
≤ Highschool	0.006	(0.014)	0.018*	(0.010)	0.014**	(0.007)
	AI		Big data		Cloud	
Non-IT Services						
Total employment	−0.223**	(0.090)	−0.150**	(0.058)	−0.102**	(0.042)
By gender						
Male	−0.065	(0.064)	−0.036	(0.037)	−0.031	(0.026)
Female	−0.158***	(0.057)	−0.114***	(0.039)	−0.071***	(0.027)
By education						
≥ Some College	−0.056	(0.094)	0.042	(0.051)	0.026	(0.037)
≤ Highschool	−0.167*	(0.089)	−0.193***	(0.056)	−0.128***	(0.043)

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.

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) and cloud computing (0.192), whereas craft and related trades face significant declines in employment due to big data (-0.380) and cloud computing (-0.212). Machine operators and assemblers show no statistically significant impact, suggesting that digital technologies in manufacturing may not yet have fully displaced manual labor beyond specific craft jobs. This result differs from findings on technological displacement due to robot adoption (Acemoglu and Restrepo, 2020; Dauth et al., 2021).

IT Services In IT services, the most pronounced effect is observed in professional and technical occupations, where employment shares decrease significantly with the adoption of all three technologies: AI (-2.629), big data (-1.586), and cloud computing (-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 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, Schubert, and Zhang, 2023). We confirm this in the next section, using data on vacancies.

Non-IT Services In the non-IT services industry, elementary occupations experience sharp declines in employment shares due to AI (-0.207), big data (-0.263), and cloud computing (-0.190). Compared with the consensus in the routinization and job polarization literature that manual, elementary occupations were less

Table 3
Impact of Digital Technology on Employment, By Occupation

	AI		Big data		Cloud	
Manufacturing						
Managers	0.000	(0.053)	0.072	(0.050)	0.033	(0.028)
Professionals and technicians	–0.196	(0.133)	0.104	(0.141)	0.096	(0.111)
Clerical support	0.255	(0.187)	0.383**	(0.189)	0.192*	(0.110)
Services	–0.004	(0.026)	–0.024	(0.024)	–0.012	(0.015)
Sales	0.059	(0.057)	0.012	(0.048)	0.019	(0.029)
Craft and related trades	0.078	(0.191)	–0.380**	(0.188)	–0.212*	(0.126)
Machine operators and assemblers	–0.133	(0.179)	–0.071	(0.175)	–0.046	(0.102)
Elementary	–0.061	(0.124)	–0.096	(0.110)	–0.069	(0.066)
	AI		Big data		Cloud	
IT services						
Managers	0.199	(0.342)	0.204	(0.255)	0.073	(0.151)
Professionals and technicians	–2.629***	(0.924)	–1.586**	(0.626)	–0.868**	(0.430)
Clerical support	1.309	(0.991)	0.847	(0.652)	0.629	(0.421)
Services	–0.003	(0.180)	0.077	(0.103)	0.079	(0.072)
Sales	0.345	(0.516)	0.444	(0.297)	0.307*	(0.188)
Craft and related trades	0.216	(0.480)	0.258	(0.372)	0.066	(0.239)
Machine operators and assemblers	0.140	(0.235)	0.102	(0.129)	0.024	(0.094)
Elementary	0.422	(0.642)	–0.344	(0.454)	–0.309	(0.320)
	AI		Big data		Cloud	
Non-IT services						
Managers	0.029	(0.033)	0.018	(0.026)	0.011	(0.019)
Professionals and technicians	–0.093	(0.181)	0.081	(0.106)	0.068	(0.082)
Clerical support	0.025	(0.118)	0.188**	(0.089)	0.104*	(0.059)
Services	0.023	(0.107)	–0.048	(0.078)	–0.027	(0.057)
Sales	–0.008	(0.118)	0.010	(0.077)	0.016	(0.056)
Craft and related trades	0.089	(0.072)	0.002	(0.044)	–0.004	(0.031)
Machine operators and assemblers	0.142*	(0.075)	0.012	(0.042)	0.024	(0.029)
Elementary	–0.207*	(0.109)	–0.263***	(0.080)	–0.190***	(0.054)

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.

vulnerable to the IT revolution, this result implies that the labor market effects of AI, big data, and cloud computing may be qualitatively different.

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, Schubert, and Zhang, 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.[7] While our findings do not pinpoint specific mechanisms, these examples illustrate how

7. 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.

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 cloud computing influence labor demand for new positions in both the manufacturing and services sectors.

Table 4
Impact of Digital Technology on Vacancies

	AI		Big data		Cloud	
Manufacturing						
Total vacancies	0.338	(0.213)	0.351	(0.211)	0.170	(0.115)
By education						
Bachelor's	0.182*	(0.088)	0.120	(0.074)	0.061	(0.039)
Master's	–0.038	(0.056)	0.064	(0.053)	0.017	(0.026)
Doctorate	0.005	(0.003)	–0.002	(0.002)	–0.001	(0.002)
By occupation						
ICT professionals	–0.010	(0.020)	0.011	(0.027)	0.005	(0.013)
Metal, machinery related trades	–0.018*	(0.010)	–0.005	(0.007)	–0.003	(0.005)
Electronic related trades	–0.001	(0.005)	–0.004	(0.006)	–0.001	(0.003)
	AI		Big data		Cloud	
IT services						
Total vacancies	0.192**	(0.084)	0.234***	(0.050)	0.148***	(0.024)
By education						
Bachelor's	0.198**	(0.079)	0.219***	(0.049)	0.139***	(0.024)
Master's	–0.003	(0.005)	0.006	(0.006)	0.002	(0.003)
Doctorate	0.002	(0.001)	0.001	(0.001)	0.001	(0.000)
By occupation						
ICT professionals	0.169**	(0.066)	0.200***	(0.040)	0.124***	(0.020)
	AI		Big data		Cloud	
Non-IT services						
Total vacancies	–0.049	(0.076)	–0.017	(0.070)	–0.024	(0.048)
By education						
Bachelor's	–0.044	(0.074)	–0.026	(0.066)	–0.026	(0.045)
Master's	–0.009	(0.007)	–0.003	(0.005)	–0.005	(0.004)
Doctorate	0.001	(0.001)	0.002	(0.001)	0.001	(0.001)
By occupation						
ICT professionals	0.014	(0.019)	0.031	(0.022)	0.020	(0.013)

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.

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.

IT Services In the IT services industry, the adoption of digital technologies 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. By educational attainment, the demand for individuals with a bachelor's degree increased the most.

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 new job opportunities.

4. CONCLUSION

This paper has examined the impact of new digital technologies—AI, big data, and cloud computing—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 female workers, marking a departure from earlier technological changes, such as the IT revolution and robot adoption, which primarily affected male 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 and technicians in IT services, and elementary occupations in non-IT 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 ICT professionals have increased even as their employment shares 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 digital economy.

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