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AI and the Labor Market

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① Artificial intelligence (AI) has been making remarkable advances over the last decade, being employed across various sectors of the economy and is expected to have an even greater impact in the future. While AI holds the potential to improve productivity, create new job opportunities, it also raises concerns about job displacement. This report examines which occupations are highly susceptible to being replaced by AI and the implications of AI for the the labor market.

② Using AI patent information, we construct occupational AI exposure indices, revealing that approximately 3.41 million workers in South Korea (12% of the workforce) face a high potential for replacement by AI technology. Unlike conventional technologies like robots and software, higher-educated and higher-income occupations are more exposed to AI, primarily due to its tendency to replace non-routine cognitive (analytic) tasks.

③ Jobs with higher AI exposure are more likely to experience a decline in within-industry employment share and a decline in wages. This projection is based on the observed decline in both employment shares and wages over the past 20 years for jobs with high exposure to robots and software. Specifically, a 10 percentile increase in the AI exposure index could potentially lead to a 7%p decrease in employment share and a 2%p decrease in wage growth over the next 20 years.

④ While new technology may displace existing jobs (displacement effect), it can also create new employment opportunities (productivity effect). Moreover, significant changes in the way tasks are performed within existing jobs may occur. The benefit of AI as a whole will depend on the adaptability of workers' skills, and how policymakers choose to support the groups that are hardest hit by these changes.

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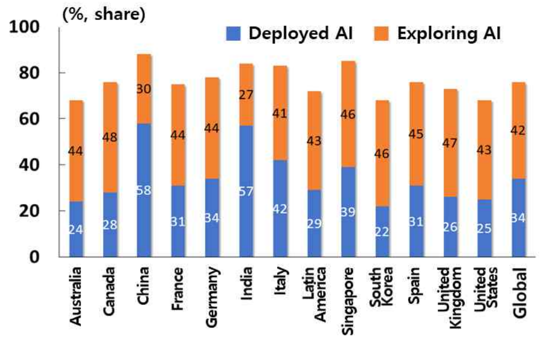
Ⅰ. Introduction

Artificial intelligence (AI) has been making remarkable advances over the last decade, being employed across various sectors of the economy and is expected to have an even greater impact in the future. AI, as a technology, identifies statistical patterns within big-data sets to perform specific tasks. It differs from conventional automation technologies (such as robots and software) as it operates based on predefined human-provided methods. AI has demonstrated superior performance in various domains compared to human capabilities. As a result, in major countries, one out of three companies has already implemented AI technology (IBM, 2022, <Figure 1>). Additionally, survey results indicate that a staggering 42% of companies plan to incorporate AI utilization in the near future.

However, the advent of new technologies inevitably creates winners and losers in the labor market. While AI has the potential to bring about improvements in productivity and work environments (McKinsey Global Institute, 2017), it also carries concerns about a jobless future (West, 2018; Suskind, 2020). In essence, while some may benefit from increased productivity due to AI, others are at risk of losing their jobs. Therefore, understanding distributional consequences is important for many purposes. For example, it allows policymakers to develop appropriate education and skill policies. In this context, this paper seeks answers to the following key questions:

- Which occupations are susceptible to AI substitution?
- What are the implications of AI for the labor market?

<Figure 1> Utilization of AI



Source: IBM Global AI Adoption Index 2022.

Ⅱ. Related Literature

As the utilization of AI increased, there's been active research on which jobs are more likely to be replaced by AI. Notably, studies such as Webb (2020) and Felten et al. (2019) utilize occupational AI exposure measures. Specifically, Webb (2020) demonstrated that high-skilled and high-wage jobs are relatively more exposed to AI using these measures. McElheran et al. (2023) presented survey results from U.S. companies showing an 'AI divide' across different company sizes. Meanwhile, Cook (2023) not only addresses job displacement due to AI adoption but also emphasizes policy efforts for job transitions, mentioning roles that could be complemented or newly created by AI technology.

Research on AI impact on jobs has been expanding in line with the expansion in AI employment. For the investigation, occupational indicators to measure AI exposure developed by Webb(2020) and Felten et al.(2019) are popularly used. Webb (2020) indicated that as the exposure indices to robotics and software increases, there's a decrease in employment share and wage growth for those jobs, suggesting a negative impact of AI on the employment and wages of replaceable jobs. On the other hand, Albanesi et al. (2023), utilizing European data, revealed an increase in the employment share of occupations highly exposed to AI. This trend was particularly prominent in occupations with a higher representation of young individuals and highly skilled workers.

Meanwhile, concerns have been raised about the potentially negative societal outcomes of unregulated AI, leading to discussions about approaches to regulate it. White House (2022) highlighted concerns regarding worsened wage inequality and ethical issues arising from AI. Acemoglu et al. (2023) emphasized policy efforts aimed at steering AI towards a 'human-complementary' path rather than evolving through negative pathways such as worker displacement and reduced bargaining power for workers. They also argued that if AI technologies evolve to create and support new tasks and skills, it could contribute to reducing inequality.

This paper utilized domestic data to examine which jobs in Korea are highly exposed to AI and presented implications regarding the impact of AI on the labor market. Specifically, we matched Webb's (2020) AI exposure index with data from the Korea Standard Classification of Occupations (KSCO) to identify occupations exposed to AI. Additionally, by using the exposure index for robot and software, we estimated the influence of AI on the employment and wages of related jobs. Finally, we laid out policy suggestions based on these implications.

Ⅲ. AI Exposure Index

1. Construction of occupational AI exposure index

Occupational AI exposure indices were utilized to examine the likelihood of certain jobs being replaced by AI technology. Among the relevant literature, the data from Webb (2020) and Felton et al. (2019) have been widely referenced. This study is based on Webb (2020) to calculate the domestic occupational AI exposure indices[1]. Webb's (2020) data provides exposure indices not only for AI technology but also for well-established technologies such as robots and software.

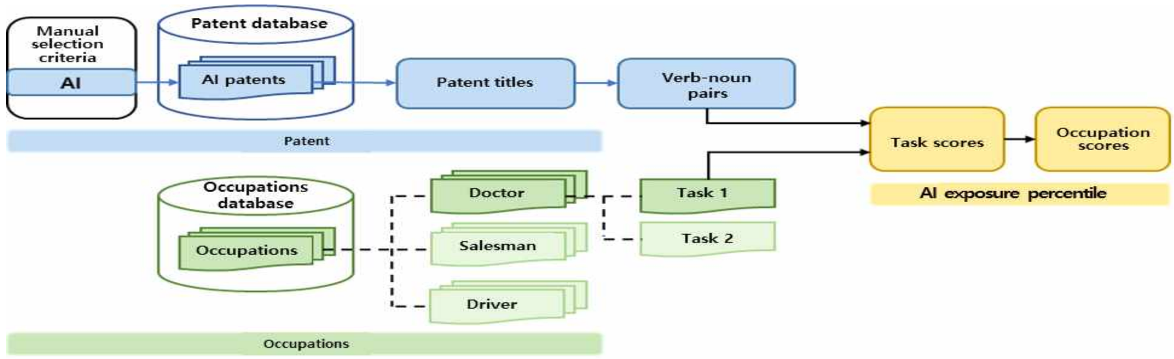
The occupational AI exposure index indicates the extent to which tasks that can

1) As explained in <Box 1>, the occupational impact measures of Webb (2020) and Felten et al. (2019) are similar. Therefore, the results obtained using the latter's approach would not have significantly differed from our findings based on the former.

currently be performed by AI technology are concentrated within the job's tasks[2]. Since a single occupation involves various tasks, the AI exposure index is initially measured at the task level. To gauge how replaceable a specific task is by AI technology, we examine the overlap between job descriptions and AI-related patent titles using verb-noun pairs (<Figure 2>)[3]. For instance, one of the primary tasks of a doctor is 'diagnose patient's condition.' To calculate the exposure index, we investigate how many AI patents contain the phrase 'diagnose condition.' After measuring task-based indices, we then calculate occupation-based indices using specific task weights for a particular occupation. Additionally, to obtain domestic occupational AI exposure indices, we converted the AI exposure indices based on the US Occupational Information Network (O*NET) to the Korean Standard Classification of Occupations (KSCO, sub-categories)[4].

Meanwhile, to anticipate the impact of AI on the labor market in future analyses, occupational exposure indices for robots and software, which significantly affect the labor market, were also computed. We employed the same approach, leveraging the texts of job descriptions and corresponding patents on robot and software technologies (Webb, 2020). Occupational exposure indices for robots and AI do not display a significant linear correlation (<Figure 3>). This implies that the jobs replaced by robots differ from those replaced by AI. Conversely, software exposure indices show a relatively strong correlation with AI exposure indices (<Figure 4>). AI, once learning algorithms are set by humans, autonomously learns from data or experiments to achieve specific goals, whereas software operates based on rules ('if-then') defined by programmers[5]. Software

<Figure 2> Constructing AI exposure index

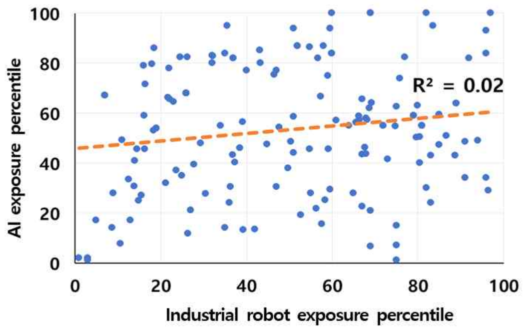


Source: Webb(2020).

2) Refer to Webb(2020) for details on the measurement.
3) Webb (2020) uses job descriptions from the O*NET database and patents from the Google Patents Public Data.
4) O*NET is revised to comply with the International Standard Classification of Occupations (ISCO) and then compared to the Korean taxonomy on occupations known as KSCO. In instances where a 1:N propensity matching is possible, we match the nearest occupation through an aggregate average of various occupations. When matching isn't possible, we find the closest tasks to match the occupation.
5) Software handles routine information processing, while AI can undertake non-routine tasks.

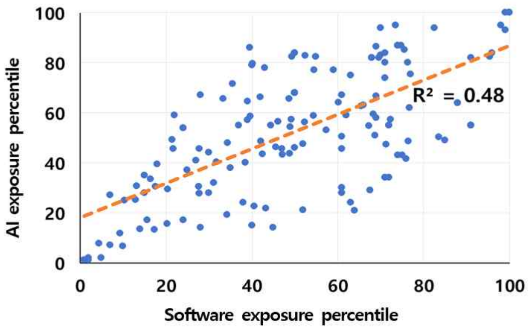
is limited to repetitive (routine) tasks, while AI can extend to non-repetitive (non-routine) tasks. However, there are instances where the distinction between AI and software, such as in autonomous driving technology, is not clear. Meaningful correlations between software and AI exposure indices seem to emerge due to the intersection between these two technologies.

<Figure 3> AI and robot exposures by occupation[1)]



Note: 1) The dotted line is the trend line.
Source: Authors' calculation.

<Figure 4> AI and software exposures by occupation[1)]



Note: 1) Dotted line is a trend line.
Source: Authors' calculation.

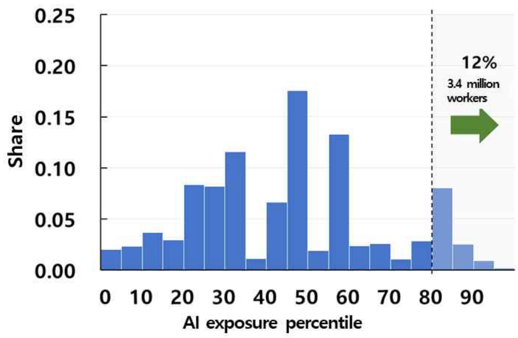
2. Which occupations are susceptible to AI substitution?

Among domestic jobs, an estimated 3.41 million positions (12% of all jobs) are deemed susceptible to replacement by AI. This estimation is derived from identifying occupations within the top 20% of AI exposure indices and summing up the number of workers engaged in these occupations. On the other hand, expanding the threshold to the top 25% would increase these vulnerable positions to around 3.98 million (14% of all jobs).

The occupations with the highest AI exposure indices include chemical engineers, power plant operators, train or subway drivers, sewage treatment technicians, waste recycling technicians, and metallurgical engineers.[6)](<Table 1>). These jobs are well-suited for optimizing tasks using large-scale data. For instance, chemical engineers are involved in designing and operating production processes, where AI algorithms could potentially replace engineers in tasks related to process optimization. Conversely, jobs with the lowest AI exposure indices, such as simple service workers or those in religious occupations, require essential face-to-face contact and relationship building.

6) In AI exposure by wage percentile, well-paid and high-skilled occupations such as general doctors, who are in the top 1% earners, specialized doctors in the top 7%, accountants in the top 19%, asset managers in the top 19%, and lawyers in the top 21%, score high. Journalists (at top 86%), clergies (at top 98%), university professors (top 98%), pop and classical singers (top 99%) show low AI exposure scores. The most and least exposed occupations to robots and software are listed in <Box 2>.

<Figure 5> AI exposure percentile



Source: KLIPS, authors' calculation.

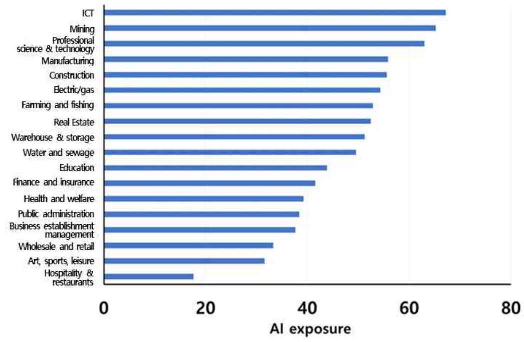
<Table 1> Most and least AI-exposed occupations[1]

Most-exposed	Least-exposed
chemical engineer	food preparation service
power plant operator	university professor, lecturer
train or subway driver	rental sales agent
sewage treatment technician	clergy
waste recycling technician	food and beverage service worker
metallurgical engineer	transportation service worker

Note: 1) Based on occupation sub-categorization (153).
Source: Authors' calculation.

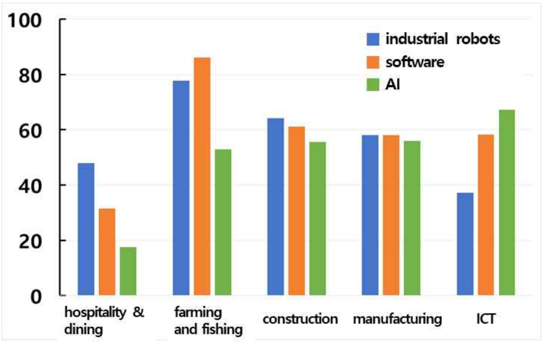
By industry, high-productivity sectors ICT, professional science and technology, and manufacturing sectors exhibited notably high AI exposure indices (<Figure 6>). In recent times, AI technology has been extensively utilized in wireless networks within the telecommunications sector, equipment monitoring solutions in manufacturing, and more[7]. Conversely, industries involving in-person services such as hospitality and dining, arts, sports, and leisure categories exhibited as expected, lower AI exposure indices. Compared to other sectors, the AI exposure index was relatively lower in accommodation and food services, whereas it was higher in ICT (<Figure 7>).

<Figure 6> AI exposure by industry



Source: KLIPS, authors' calculation

<Figure 7> Exposure to technologies by industry



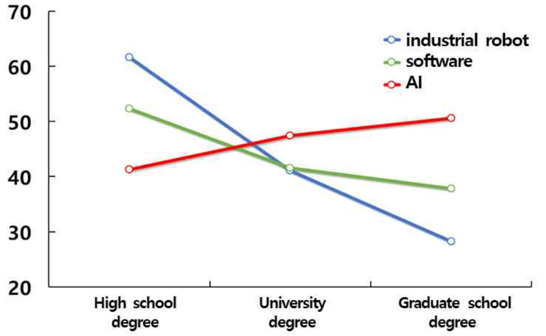
Source: KLIPS, authors' calculation

Regarding wage and education levels, higher-educated and higher-income workers tend to have greater exposure to AI (<Figures 8, 9>). This notably differs from other technologies like robots and software, which had a more significant impact on lower-educated (high school or below) and mid-income workers. It's estimated that

7) In Korea, AI is being used to inspect new car bodies and monitor chip fab processing.

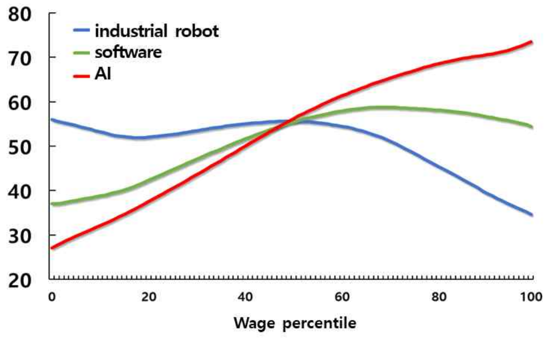
occupations performing non-routine cognitive analytic tasks, which AI can substitute for in non-routine cognitive tasks[8], are more exposed to AI. There's a considerable risk of AI substitution in high-educated and high-income jobs. This suggests the impact on the labor market from wider AI adoption can pan out in different form than earlier technologies.

<Figure 8> Technology exposure by education level



Sources: KLIPS, authors' calculation.

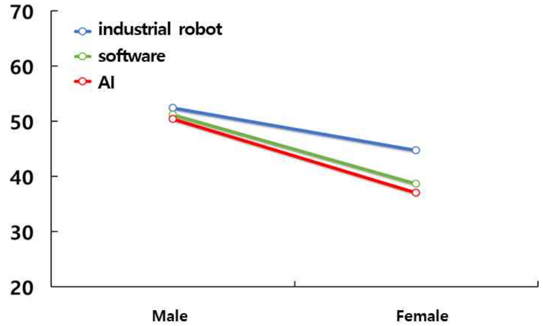
<Figure 9> Technology exposure by wage percentile[1)]



Note: 1) Locally weighted smoothing regression. (bandwith 0.8)
Source: KLIPS, authors' calculation.

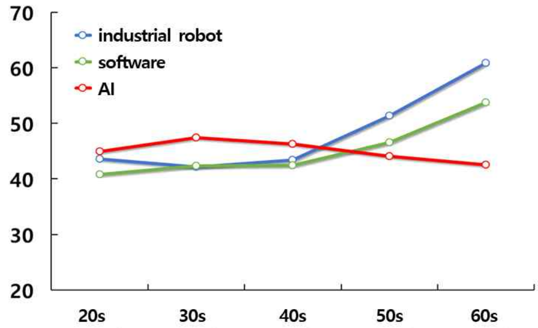
When examining gender, the AI exposure index for male jobs appears slightly higher compared to female jobs. Similar to industrial robots or software technologies, male jobs show greater exposure to AI, possibly due to a relatively higher female presence in face-to-face service industries, which tend to have lower AI exposure indices. However, there wasn't a clear distinction observed in AI exposure indices across different age groups.

<Figure 10> Technology exposure by gender



Sources: KLIPS, authors' calculation.

<Figure 11> Technology exposure by age



Source: KLIPS, authors' calculation

8) Webb(2020) presents the average of standardized occupation-level exposure scores by weighted tasks using a locally weighted smoothing regression (<Box 3>). Non-routine cognitive tasks are assumed to be more exposed to AI.

IV. AI impact on the labor market

AI is a rapidly advancing technology, and its utilization by businesses is still in its early stages[9]. Therefore, rigorously analyzing the impact of AI on the labor market at this stage is challenging. There's significant uncertainty about how AI technology will evolve in the future and how it will integrate into individual industries. For instance, recent advancements in generative AI, like the advent of ChatGPT, signify the swift development in AI-related technologies. Additionally, the regulation surrounding AI remains a subject of ongoing debate.

The development has stoked a flurry of studies on the potential impact on the labor with data attainable so far. Acemoglu et al.(2020) discovers from data on online vacancies that AI-exposed establishments reduce hiring in non-AI positions as well as overall new hiring to suggest AI is altering the task structure of jobs and hiring scale in line with AI substitution[10]. Hui et al.(2023) observes short-term impact of reduced demand and earnings for knowledge workers from the release of the large language model ChatGPT. Webb(2020) postulates AI adoption could bring about declines in within-employment and wage from the exposure to the new technology in the same historic pattern with the adoption of industrial robots and software.

Utilizing the methodology outlined by Webb (2020), this study examined the impact of the onset of robots and software on the domestic labor market, aiming to infer the potential implications of AI adoption. Specifically, empirical analyses were conducted to investigate the impact of robots and software introduction on employment and wages over the past two decades (2000 to 2021). Regression equations were estimated by comparing occupation-industry-year cells (based on industry and occupation mid-classifications) between 2000 and 2021.

$$\Delta y_{o,i,t} = \alpha_i + \beta Exposure_o + \gamma Z_{o,i} + \epsilon_{o,i,t}$$

$\Delta y_{o,i,t}$ denotes the changes in employment and wage between 2000 and 2021. To measure the change in employment, we multiplied 100 to the DHS change[11] of employment shares between 2000 and 2021 cells. To identify the change in wages, we multiplied 100 to the log difference of the average of wages in each cell unit. $Exposure_o$ is the exposure of the occupation to robots or software, $Z_{o,i}$ contains the industry fixed effects and wage

9) According to the Mckinsey Global Survey (2023), the adoption of AI in companies has more than doubled from 20% in 2017 to 50% in 2022. Additionally, 40% of respondents stated that their organizations would further increase investment in AI.

10) Acemoglu et al.(2020) conclude that despite the surge in AI adoption, its impact remains relatively small in comparison to the scale of the US labor market, thus not significantly affecting employment patterns beyond AI-related hiring itself.

11) DHS is a symmetric measure of the growth rate defined as the difference of two values s_1, s_0 divided in the form of $2 \times (s_1 - s_0)/(s_1 + s_0)$. Based on the literature Davis et al.(1996), Webb uses DHS change instead of log change to reflect zero-valued observations such as new and obsolete jobs.

level of occupations (based on 2000 data). The analytical data utilized the Korea Labor and Income Panel Study (KLIPS)[12]. In the case of robots, due to limited utilization in the service sector, the estimation was restricted to the manufacturing industry. As for software, the estimation was conducted across whole industries.

Regarding robots, it was observed that when the exposure index increases by the 10th percentile, employment share decreases by 12%p, and the wage growth rate decreases by 5%p. Since the observation is based on within-industry effect, specific manufacturing occupation exposed to robots were more affected than those unexposed to automation. This aligns with the findings of Acemoglu & Restrepo (2020) regarding the employment and wage reductions due to robots. Webb (2020) also demonstrated, using U.S. data, that jobs with higher exposure indices to robots show significant decreases in employment share and wage growth. However, in comparison to the U.S., the reduction in employment and the slowdown in wage growth due to the introduction of robots appeared relatively more pronounced in Korea[13]. This difference is attributed to Korea's leading position in the adoption of robots in manufacturing globally. Korea's high utilization of robots, particularly in sectors like semiconductors and automobiles, appears to have significantly impacted the labor market[14].

<Table 2> Estimation results: robots[1)]

	Employment		Wage	
	(1)	(2)	(1)	(2)
$Exposure$	-1.194***	-1.166***	-0.018	-0.462***
Wage		-2.236*		-0.816*
Wage^2		0.012**		0.000
Industry fixed effects	O	O	O	O
R^2_{adj}	0.352	0.392	0.188	0.545
Samples	63	63	63	63

Note: 1) * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
Sources: KLIPS, authors' calculation.

With software, 10th percentile of exposure relates to declines of 7%p in within-industry employment share and 2%p in wage growth rate. The results once again are congruous with the finding with U.S. data in Webb(2020). However, the estimated negative impact on the labor market appeared to be relatively smaller compared to the effects of robots.

12) Although the Economical Active Population Survey has greater number of samples, it only provides industrial and occupational information in big categories.
13) In the US, 10th percentile exposure to robots is associated with 3.6%p drop in within-industry employment share and 2.8% fall in wage growth rate(Webb, 2020).
14) In the World Robotics 2022 Report of International Federation of Robotics (IFR), the manufacturing sector in South Korea employs 1,000 industrial robots per 10,000 employees in 2021. Singapore, ranking second, utilizes 670 robots per 10,000 employees, while Japan, ranked third, employs 399 industrial robots per 10,000 employees, showcasing a significant difference compared to South Korea.

<Table 3> Estimation results: software[1)]

	Employment		Wage	
	(1)	(2)	(1)	(2)
$Exposure$	-0.730**	-0.735***	-0.208	-0.235*
Wage		-0.916		-1.344***
$Wage^2$		0.005*		0.003 **
Industry fixed effects	O	O	O	O
R^2_{adj}	0.218	0.236	0.115	0.428
Samples	154	154	154	154

Note: 1) * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
Source: KLIPS, authors' calculation.

Considering the decrease in relevant jobs and the decreased wage growth from the adoption of robots and software, AI can bring about similar negative impact on the jobs susceptible to AI substitution. Based on the positive correlation with software, we can assume 10th percentile exposure to AI can lower sector-employment share by 7%p and slow wage growth rate by 2%p[15)].

However, new technology not only displaces existing jobs but also creates new ones. There's an increase in high-productivity jobs involved in developing and maintaining AI technology, including startups focused on AI-related innovations. Moreover, the productivity boost due to AI could lead to overall increased labor demand and wage growth. Nevertheless, since productivity improvement impact on the overall economy from technology diffusion can be limited, whereas the displacement is concentrated on certain groups, concerning workers can face hardship in relocation after AI takes over their jobs.

V. Other issues

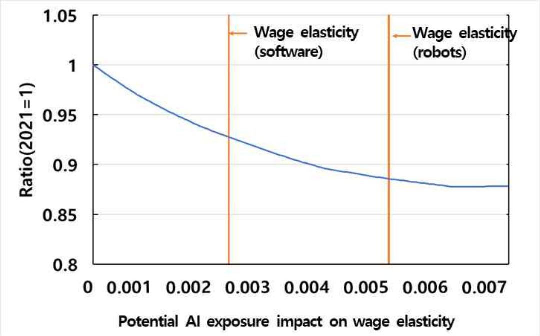
1. Wage inequality

Various discussions exist regarding how AI might influence wage inequality. This study calculated the changes in wage distribution resulting from AI adoption, based on the estimation that there's a negative relationship between the AI exposure index and wage growth (Webb, 2020). Using the AI exposure index by occupational classifications and wage data (as of 2021), the study calculated the occupational wage levels $(wage * e^{-\beta \cdot exposure})$[16)]. Subsequently, it determined the wage distribution across occupations to derive the 90:10 ratios and the Gini index.

The simulation results indicated a reduction in both the 90:10 ratios[17)] and the Gini coefficient, suggesting a mitigated wage inequality due to AI implementation. According to <Figure 12>, assuming a similar wage elasticity to that of software, the 90:10 ratio is estimated to decrease by 7% following AI adoption. Furthermore, the Gini coefficient is projected to decrease from 0.20 to 0.18 with the diffusion of AI (<Figure 13>).

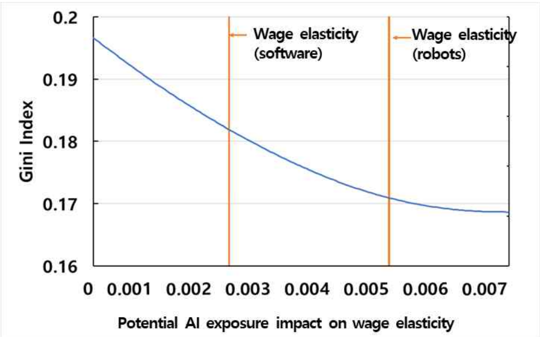
15) However, it's essential to note that these findings may vary based on the development trajectory of AI technology and the introduction of regulations.
16) β represents the wage elasticity coefficient and the magnitude of β influences the measure of wage inequality.
17) The 90:10 ratio divides the ratio of top 10% income in the decile to that of the bottom 10%.

<Figure 12> The 90:10 ratio based on wage elasticity



Source: KLIPS, authors' calculation

<Figure 13> Gini Index based on wage elasticity



Source: KLIPS, authors' calculaton

However, research suggests that wage inequality could worsen due to AI, contrasting the aforementioned simulation results. Acemoglu (2021) argues that due to imperfections in the labor market, firms may use AI technology to replace workers and transfer worker gains to firm profits. In essence, automation using AI could increase corporate profits while reducing income for wage workers, negatively impacting wage inequality. Additionally, White House (2022) has raised concerns that unregulated AI could exacerbate wage inequality by intensifying outsourcing strategies. Increased outsourcing due to AI could spur competition among subcontractors, leading to decreased wages for low-paying jobs, consequently deepening wage inequality.

2. AI Regulation

The fast advance in AI has sparked discussions about adverse social consequences. It is feared to cause a wide range of concerning issues from not just inequality, but also weakening in consumer protection and democracy functions while feeding corporate greed.

Companies can exploit on consumer welfare through avaricious collection of information to manipulate consumer behaviors in their favor. Big data and algorithm technologies can easily track and analyze consumer behaviors, allowing companies to use them for price discrimination and other disadvantages against consumers. Data externality from the abundance of information falling in the hands of companies has adverse implications for privacy and consumer surplus.

AI replacing human force can have broad negative ramifications on the society and democratic institutions. Automation can shift power away from labor onto capital to cause far-ranging impacts on the democratic functions. When AI is trained on biased data, it can feed misinformation and fragmentation.

Since AI can bring both economic benefits and social harms, there must be sufficient discussions on AI developments and regulations. Acemoglu(2021) argues AI should be properly regulated, given the explosive and wide-reaching potential of the technology. He predicts if AI accelerates in current pace, the political and social costs could be impossible to reverse once they are fully realized, and advises "precautionary regulatory principle" to slow the use of AI in domains where redressing the costs after large-scale implementation can be difficult. McElheran et al.(2023) express concern about the potential rise in "AI divide" from the uneven spread of AI in the initial phase as the usage is concentrated in tech hubs in California and some selective areas. If the clustering and divide deepen, they worry a few companies can dominate the benefits and widen the gap with those slower and late in adoption. Policymakers must therefore deliberate on the regulations to direct AI technologies in a way to bolster opportunities and capabilities for broad economic participants.

VI. Conclusion and implications

This paper explores occupations with greater propensity to be replaced by AI based on patent and job descriptions related to AI technologies. Occupations whose tasks have the potential to surrender to AI are estimated at 3.41 million, or 12% of jobs available in Korea. Unlike earlier automation technologies of robots and software, high-income and highly-educated workers are more vulnerable to AI displacement.

The potential impact of AI on the labor market indicates that jobs with higher AI exposure indices are expected to experience decreased employment shares and lower wage growth. This expectation is based on estimations that over the last 20 years, as exposure indices for robots and software increased, there was a corresponding decrease in employment rates and a slowdown in wage growth for those jobs.

However, new technologies also create new tasks and job opportunities. Moreover, increased productivity due to AI can lead to overall growth in labor demand and wage increments. Yet, while productivity impacts the entire economy, the effects of displacement are more concentrated within specific groups. This underscores the urgent need for shifts in education and training programs. Ultimately, the magnitude of benefits our society reaps from AI seems heavily contingent on the adaptability of the workforce and policy design.

Meanwhile, the introduction of AI will demand different skill sets from the workforce. While the demand for STEM (Science, Technology, Engineering, Mathematics) skills is expected to remain robust, there's also an anticipated significant increase in the demand for soft skills. Given AI's ability to replace not just repetitive tasks but also cognitive functions where traditional techniques fall short, there's a likelihood that soft skills[18] such as social skills, teamwork, and communication may receive greater recognition (Deming, 2017b).

Finally, while AI brings convenience to both work and daily life, proactive consideration regarding appropriate regulations is crucial. This proactive approach becomes essential due to the potential negative societal impacts such as reduced consumer welfare and increased profit monopolization that AI could bring about.

18) According to Deming (2017a), the proportion of jobs requiring social skills increased by 12% between 1980 and 2012, and the labor market return for social skills was significantly higher in the 2000s compared to the 1990s.

<Box 1>

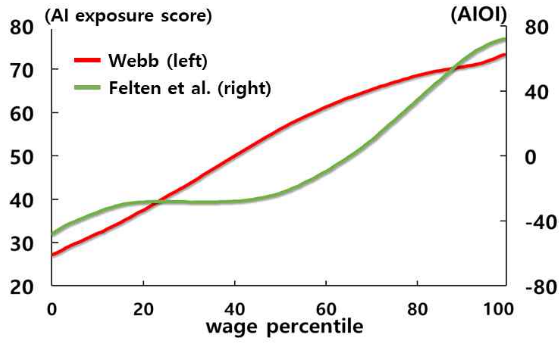
AI Impact Measurements on Occupations: Webb(2020) vs. Felten et al.(2019)

Webb(2020), which measures AI exposure in occupations based on patent data, and Felten et al.(2019), exploring AI Occupational Impact (AIOI), are widely cited in studies analyzing the innovation's impact on the labor market.

AIOI is calculated to connect specific AI applications to various occupations by considering labor as a blend of technology and capability. It is built on the dataset of the Electronic Frontier Foundation AI Progress Measurement, which tracks reported advancements in AI performance metrics across distinct applications like image recognition, speech recognition, translation, or abstract strategy games, along with the collection of job descriptions available on the Occupational Information Network (O*NET).

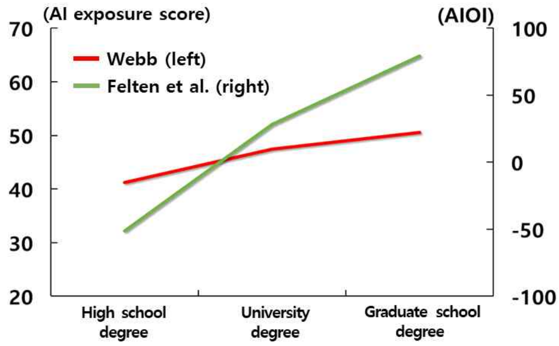
Both measurements yield similar outcomes after comparing the Webb AI exposure indicator utilized in this paper with the AIOI, subsequent to aligning and matching with the Korean Standard Classification of Occupations. As depicted in [Figure 1-1, 1-2], both the AI exposure indicator and AIOI highlight a greater impact on high-income and highly educated workers due to AI exposure.

[Figure 1-1] AI exposure score and AIOI[1] by wage



Note : 1) Locally wieghted smoothing regression(bandwith 0.8).
Sources: KLIPS, authors'calculation.

[Figure 1-2] AI exposure score and AIOI by education



Sources: KLIPS, authors'calculation.

<Box 2>

Most and Least Technology-exposed Occupations

[Table 2-1] Exposure to robots[1)]

Most exposed	Least exposed
Train and subway driver	Clergy
Cleaner	Professor and lecturer
Building structure engineer	Rental agent
Metal plating technician	Online sales agent
Forklift driver	Insurance, finance agent
Operating engineer for cranes, derricks, etc.	Payroll and bookkeeping clerk

Note: 1) Based on occupation sub-categorization (153).
Source: Authors' calculation.

[Table 2-2] Exposure to software[1)]

Most exposed	Least exposed
Power generating and distribution technician	Professor and lecturer
Train and subway driver	Rental agent
Water and sewage treatment plant operator	Food sorting and other simple worker
Recycling and waste treatment plant operator	Security worker
Chemical plant engineer and supervisor	Clergy
Forklift driver	Shipping service worker

Note: 1) Based on occupation sub-categorization (153).
Source: Authors' calculation.

<Box 3>

Comparisons to Autor et al.(2003)

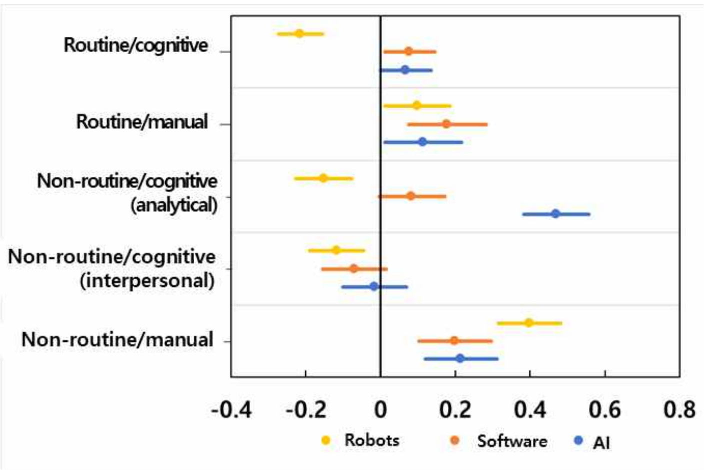
Webb(2020) refers to the definitions provided by Autor et al.(2003) to distinguish tasks susceptible to automation by industrial robots, software, and AI based on characteristics such as 'routine versus non-routine' and 'manual versus cognitive'. These features are scored as predictor variables to determine the following regression equation.

$$\begin{aligned} Exposure_{i,t} = \; & Routine\,Cog_i + Routine\,Man_i + \\ & NonRoutine\,CogA_i + NonRoutine\,CogI_i + NonRoutine\,Man_i + \epsilon_{i,t} \end{aligned}$$

$\mathrm{Exposure}_{i,t}$, $Routine\,Cog_i$, $Routine\,Man_i$, $NonRoutine\,CogA_i$, $NonRoutine\,CogI_i$, $NonRoutine\,Man_i$ respectively represents the exposure to each technology, categorized by task features of routine and cognitive, routine and manual, non-routine and cognitive, non-routine and cognitive (analytical), non-routine and cognitive (interpersonal), and non-routine and manual.

Tasks requiring non-routine, cognitive (analytical) skills exhibit a higher level of susceptibility to AI. This implies that, compared to other automation technologies, AI is better suited for replacing non-routine, cognitive, and analytical tasks.

[Figure 3-1] Regression results on technology exposure and task capabilities[1)]



Note: 1) Regression estimate with a 95% confidence interval.
Source: Webb(2020).

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