

Article

Does Artificial Intelligence Promote or Inhibit On-the-Job Learning? Human Reactions to AI at Work

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Abstract: This paper examines how AI at work impacts on-the-job learning, shedding light on workers' reactions to the groundbreaking AI technology. Based on theoretical analysis, six hypotheses are proposed regarding three aspects of AI's influence on on-the-job learning. Empirical results demonstrate that AI significantly inhibits people's on-the-job learning and this conclusion holds true in a series of robustness and endogeneity checks. The impact mechanism is that AI makes workers more pessimistic about the future, leading to burnout and less motivation for on-the-job learning. In addition, AI's replacement, mismatch, and deskilling effects decrease people's income while extending working hours, reducing their available financial resources and disposable time for further learning. Moreover, it has been found that AI's impact on on-the-job learning is more prominent for older, female and less-educated employees, as well as those without labor contracts and with less job autonomy and work experience. In regions with more intense human–AI competition, more labor-management conflicts, and poorer labor protection, the inhibitory effect of AI on further learning is more pronounced. In the context of the fourth technological revolution driving forward the intelligent transformation, findings of this paper have important implications for enterprises to better understand employee behaviors and to promote them to acquire new skills to achieve better human–AI teaming.

Keywords: artificial intelligence; on-the-job learning; technological revolution; replacement effect; deskilling effect



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1. Introduction

Artificial intelligence, as the core driving force of the fourth technological revolution, has grown by leaps and bounds in recent years. According to 2022 International Federation of Robotics (IFR) statistics, the number of new industrial robots installed worldwide reached an all-time high of 517,385 in 2021, with a yearly growth rate of 31%. Over the past six years, annual robot installations have more than doubled (<https://ifr.org/worldrobotics/> accessed on 16 January 2023). The rapid development of AI brings immense economic benefits [1–3] and profound changes in people's preferences and behaviors [4]. From an enterprise perspective, the new work pattern applying AI contributes to wiser organizational decisions [5], better innovation management [6], and performance improvement [7]. From the viewpoint of workers, the new work style teaming with AI deeply influences their employment [8,9], income [10], and well-being [11]. However, how workers react to the AI technological revolution at work remains an unanswered question. It is yet to be determined whether workers tend to further improve their skills to enhance competitiveness against AI, or whether they passively accept AI's replacement and deskilling effects on their jobs, resulting in a decrease in further learning.

On the one hand, the stimulation effect of artificial intelligence may motivate workers to further improve skills so as to avoid being replaced by the new technology [12]. AI's

complementarity and cost-saving effects can also increase people's income [13,14]. In addition, the productivity and replacement effects of AI may reduce employees' working hours [15–17]. All of these factors can help to promote people's on-the-job learning. However, on the other hand, AI may also lead people to have more pessimistic expectations about the future by substituting their jobs, as well as bringing about a burnout effect [18,19], which undermines their motivation for further learning. In addition, AI has the replacement effect [8], mismatch effect [20], and deskilling effect [21,22] on people's jobs, decreasing their financial resources and time available for on-the-job learning.

Therefore, based on a theoretical analysis, it is unclear whether artificial intelligence promotes or inhibits on-the-job learning. In the current context of the booming AI technology and digital transformation of industries, promoting employees to learn new skills that can facilitate collaborating with AI is crucial for enterprises to improve their competitiveness [23,24]. In light of this, this paper empirically examines the impact of AI on on-the-job learning using the data from the Chinese general social survey (CGSS). In addition, this study conducts a series of robustness and endogeneity tests by applying different AI and on-the-job learning measures, ordered response models, instrumental variables approach, penalized regressions, placebo tests, etc. We also systematically explore the future expectation, economic income, and working-time mechanisms through which AI affects on-the-job learning. Furthermore, the heterogeneities of AI's influence in terms of demographic, working, and regional characteristics are further explored.

The contributions of this paper include the following aspects. First, this paper deepens our understanding of human reactions to artificial intelligence at work from an on-the-job learning perspective and expands the research concerning AI's impact on workers. Existing studies about the impacts of AI on workers have mainly focused on its direct effects on employment [8,9,25], income [10], and well-being [11,26]. However, there is a lack of literature on how workers react to AI. This paper provides a valuable exploration in this regard. The findings of this paper reveal that workers passively accept the effect of AI and reduce on-the-job learning. This can help companies to better understand employee preferences and behaviors while taking advantage of AI for technological upgrades. Second, this paper examines factors influencing employees' on-the-job learning from a novel perspective of technological change and clarifies the impact mechanism of technological progress on on-the-job learning. There are numerous elements affecting on-the-job learning, and the related literature has mainly emphasized factors with respect to organizational environment [27], job attributes [28,29], demographic characteristics [30,31], as well as personal traits [32]. Nevertheless, the effects of technological advances on on-the-job learning have been relatively neglected. Therefore, this study contributes to a more comprehensive understanding of the elements influencing on-the-job learning from a new view. In addition, this study indicates that by creating more pessimistic expectations, reducing income, and extending work hours through its deskilling effect, AI inhibits workers' on-the-job learning. Thus, this paper enlightens enterprises to optimize their management strategy from the perspectives of workers' expectations, earnings, and working hours, so as to motivate workers to learn further, improve human capital, and promote innovation. Third, this paper also identifies vulnerable subgroups whose on-the-job learning is more adversely affected in the era of AI, such as older, female and less-educated workers, as well as those with less job autonomy and work experience. This contributes to encouraging enterprises and governments to pay more attention to these employees and consider providing them with more training opportunities and labor protection.

The remainder of the paper is structured as follows: Section 2 is the literature review and theoretical background. Section 3 introduces data and variables. Section 4 presents the results of benchmark analysis, as well as endogeneity and robustness tests. Section 5 explores impact mechanisms through which artificial intelligence affects on-the-job learning. Section 6 conducts heterogeneity analysis. Section 7 summarizes the findings of this study and puts forward implications.

2. Literature Review and Theoretical Background

2.1. AI's Impacts on People's Future Expectations and On-the-Job Learning

The previous literature has shown that the growing power of artificial intelligence and its increasing status in the workplace may make workers more pessimistic about their future. According to Huang and Rust [33], both humans and AI have four intelligences: mechanical, analytical, intuitive, and empathetic intelligences. Mechanical intelligence is responsible for standardized and repetitive tasks. Analytical intelligence is the ability to process information and to perform tasks requiring logical thinking in decision-making. Intuitive intelligence completes tasks needing intuitive, holistic, experiential, and contextual interactions. Empathetic intelligence is applied for tasks that involve empathy and emotional analytics. Although currently humans have the advantage in the “softer” intuitive and empathetic skills [33,34], with the rapid development of enhanced computing power and machine learning algorithms, AI can learn and accumulate knowledge on its own, just like human capital [35]. Thus, it is suggested that AI will replace people to perform complex tasks requiring the latter two intelligences [33]. In addition, the power of AI is also reflected in its increasing importance and status at work [4–6], where the role of AI gradually changes from follower to manager [36,37] or even leader [38,39], leaving workers with less room for further promotion. Because of the above reasons, humans may perceive AI as a threat to their jobs, leading to increased fear of unemployment, anxiety [40], and job insecurity [26]. Lan et al. [41] find that when human employees feel threatened, they may develop robot-phobia and have more pessimistic expectations about the future due to AI-induced displacement of their jobs.

When workers perceive their roles as vulnerable to being replaced by artificial intelligence and have pessimistic expectations, the existing literature does not provide a definitive answer as to whether they are stimulated to further improve their skills to enhance competitiveness or whether they become burned out and reduce on-the-job learning. A strand of literature believes that the threat brought by new technologies stimulates workers to learn more to update their knowledge. Ivanov et al. [12] find that when faced with a potential threat of substitution, employees prefer the “fight strategy”, in which they learn how to use new technologies to be more productive to stay competitive. In addition, it is also shown that people with job insecurity are more willing to undertake training to strengthen their ability to find jobs outside the organization [32]. At the same time, the improvement of skills enables workers to build confidence in their employability, thus increasing job satisfaction and security [42]. Therefore, Hypothesis 1a can be proposed: the pessimistic expectations caused by AI have a stimulation effect and thus promote on-the-job learning. However, on the other hand, when employees feel fear of unemployment and the negative emotions dominate, AI may lead to burnout, thus discouraging further learning [18,19]. This is because people may perceive themselves as no longer competitive against AI and that human capital has been totally replaced by AI. Hence, people have a sense of hopelessness in achieving better performance at work than AI even if they engage in further learning [43]. Based on this, Hypothesis 1b, which is the opposite of Hypothesis 1a, can be put forward: the pessimistic expectations caused by AI have a burnout effect and thus inhibit on-the-job learning.

2.2. AI's Impacts on Workers' Income and On-the-Job Learning

In addition to affecting future expectations, artificial intelligence can also impact workers' income. Nevertheless, studies have not reached a unanimous conclusion as to whether AI increases or decreases income. A stream of research argues that AI is labor-friendly and raises income. First, AI has a complementarity effect on labor demand. When AI is applied in production, it requires close collaboration with human cognitive and interpersonal skills, thus promoting the employment and income of workers with such skills [13,14]. Moreover, this will motivate workers to seek further learning and training to acquire these skills to achieve better human–AI collaboration, and therefore, increase wages [44]. In addition, AI also has a cost-saving effect. The application of automation can

save production costs, lower the price of products and increase total demand, creating more demand for labor and thus resulting in increased incomes [45]. Therefore, on the grounds of its complementarity and cost-saving effects, AI may exert a positive effect on income.

However, another stream of research holds the view that artificial intelligence reduces workers' income, mainly due to the following two reasons. First, AI has a capital-deepening effect and brings down labor demand, which leads to job replacement and lowers earnings for workers [8]. For example, it has been found that in the human-machine competition, automation brought by AI displaces labor and decreases its wage [16]. Second, AI can also exert a mismatch effect on the labor market. Despite the aforementioned complementarity effect, skills in the workforce may not suit the requirements of the new technology in the short term. Consequently, AI can lead to a mismatch between labor skills and the demands of new technologies, thus reducing economic gains from AI application [20]. Furthermore, the AI-induced mismatch creates a higher risk of frictional unemployment and lowers workers' income [10,25]. Therefore, from the theoretical analysis, the impact of AI on people's income is unclear. On-the-job learning entails financial resources as well as opportunity costs in lost income. If AI raises employees' income, they can shoulder higher costs of on-the-job learning, and thus increase the frequency of their on-the-job learning. In view of this, Hypothesis 2a can be proposed: AI's complementarity and cost-saving effects increase income and thus promote on-the-job learning. On the contrary, if AI decreases people's income, there will be less financial resources available for training, resulting in reduced on-the-job learning. So, Hypothesis 2b, opposite to Hypothesis 2a, can be proposed: AI's replacement and mismatch effects reduce income and thus inhibit on-the-job learning.

2.3. AI's Impacts on Employees' Working Hours and On-the-Job Learning

On-the-job learning, which is a form of human capital investment, not only requires financial expenses but also involves investment in time. Therefore, exploring the impact of artificial intelligence on further learning also requires clarifying the relationship between AI application and working time. There are two opposite viewpoints on this issue in the existing literature. On the one hand, some studies suggest that AI deskills workers and reduces their bargaining power [46]. As a consequence, AI may extend working hours. To be specific, with the standardization of work tasks realized by advanced technologies, it is no longer necessary for experienced and skilled workers to perform complicated tasks at work. As a result, their skills could not automatically give them bargaining power in the workplace [21,22]. Therefore, people's working hours may increase because of their reduced negotiating power. Moreover, employees' control over their work also decreases due to AI-driven deskilling [47]. Machines can work at more intense rhythms and increase human workload and working time [48,49]. In this process, AI can also manage and monitor work processes in real time [50], resulting in employees experiencing more work stress. In addition, from a macroeconomic perspective, technological advances may also increase working hours. This is due to the fact that, based on the real business cycle theory, favorable technological advances can drive investment, which requires more labor input [51].

However, on the other hand, some research demonstrates that artificial intelligence may reduce working time. First, AI has the productivity effect. It can support workers in performing repetitive and heavy tasks and the human-machine cooperation saves working time [52]. Therefore, the application of AI directly improves productivity [2,53]. Moreover, technological upgrading promotes labor reallocation, for which AI also indirectly promotes productivity [15]. Owing to the lifted productivity, people's working hours may decrease. Second, AI has the replacement effect discussed earlier, which can decrease people's work on certain tasks, thereby shortening working hours [16,17]. For example, Cho and Kim [54] find that AI application in some Korean firms helps to reduce overwork. According to the above literature, AI may either decrease or increase working hours. If AI increases working time due to its deskilling effect, workers would have less time available for learning, and thus, their on-the-job learning would be less frequent. This leads to Hypothesis 3a: AI's deskilling effect increases working hours and thus inhibits on-the-job learning. Conversely,

if AI reduces working hours thanks to its productivity or substitution effects, then workers can spare more time to learn new skills. From this, Hypothesis 3b can be put forward: AI's productivity and replacement effects reduce working hours and thus promote on-the-job learning.

2.4. Possible Heterogeneities in AI's Effects on On-the-Job Learning

From the existing literature, there may exist heterogeneities in the effects of artificial intelligence on on-the-job learning across different groups. First, the impact of AI on on-the-job learning may vary depending on demographic characteristics. In terms of age, younger workers are more willing to acquire new knowledge and skills, whereas the older labor force is less able to adapt to technological changes, and thus, more likely to be replaced by AI [55]. Moreover, the accelerating pace of technological progress and innovation increases the demand for work-related learning. However, as people age, their motivation to learn diminishes. As a consequence, employers are more willing to provide more training and development opportunities to younger workers [56,57]. For these reasons, older employees' willingness to learn on the job may decrease to a greater extent when their jobs are impacted by AI. Regarding gender, studies find that women tend to perform routine tasks more often than men even within the same occupational category, making them more at risk of being substituted [58]. Furthermore, women are more vulnerable to labor market discrimination in terms of job search, promotion opportunities, and payment for labor [59]. Therefore, it is more difficult for them to switch jobs by updating skills when being replaced by new technology. In terms of education, those with higher levels of education are less likely to be displaced by AI [25]. Zhou et al. [60] have discovered that for those with college and above educational attainment, the substitution probability is only half of that of low-education groups. Furthermore, educational level is usually positively correlated with a willingness to participate in work-related learning [31]. Hence, in the face of AI's replacement effect, workers with lower levels of education may be less inclined to learn on the job.

Second, the impact of artificial intelligence may differ based on working characteristics. Labor contracts are the legal basis for workers to protect their rights and interests. They can raise social insurance coverage and reduce the likelihood of wage arrears, thus improving the welfare of underprivileged labor [61,62]. All these factors contribute to mitigating the impact of AI on workers. Therefore, labor contracts may reduce the impact of AI at work on on-the-job learning. With regard to job autonomy, related studies have shown that granting workers more autonomy to determine their work content increases their willingness to learn [63]. Conversely, less job autonomy not only decreases willingness to learn but also increases turnover intention [64,65]. In addition, work experience can enhance employability [66], which helps workers better switch jobs when they are replaced by AI. Consequently, the effect of AI on on-the-job learning may be smaller for those with higher job autonomy and more work experience. Third, macro-level regional factors may also play a role in the impact of AI on workers' on-the-job learning. In regions with faster technological development, workers often develop more negative emotions, such as anxiety, insecurity, and aversion to new technologies [67]. As a result, they may react more passively to technological progress, reducing on-the-job learning to a greater extent. In contrast, in regions with stronger labor protection, workers tend to have a more positive attitude toward new technology. They are also more likely to adapt to rapidly evolving skill demands through reeducation and retraining [68]. From the above analysis, the impact of AI on workers' on-the-job learning can vary in regions with different levels of technological development, AI application, and labor protection.

Based on the above analysis, the theoretical framework and research design of this study are illustrated in Figure 1.



Figure 1. Theoretical framework and research design.

3. Data and Variables

3.1. Data Source

This paper examines the impact of artificial intelligence on employees’ on-the-job learning using data from the Chinese general social survey (CGSS). CGSS is the first nationwide, comprehensive, and continuous large-scale survey project in China, aiming to systematically collect multi-dimensional information at the individual level and monitor changes in society. Compared with other data sources, CGSS has two advantages for this study: first, CGSS investigates respondents’ on-the-job learning frequencies and comprehensive factors influencing further learning, facilitating the construction of the dependent and control variables of this research. Second, CGSS provides people’s occupational codes of the international standard classification of occupations 2008 (ISCO-2008), which enables us to measure AI’s impact on respondents’ work, so as to construct the explanatory variables of this paper. CGSS data have been updated to 2018; however, since the ISCO-2008 standard occupational codes are not available in the data before 2017, this paper uses the 2017–2018 wave data in CGSS.

3.2. Variables

3.2.1. Dependent Variables

The main dependent variable in this paper is the frequency of on-the-job learning, derived from the responses of employed respondents to the frequency of further learning, denoted as *Further_Learning_i*. Specifically, the frequency of further on-the-job learning is measured based on the five-point Likert scale, classifying learning frequency from 1 to 5 as “never”, “seldom”, “sometimes”, “often”, and “frequently”. Higher scores indicate more frequent on-the-job learning. This indicator has been used in many existing studies to characterize workers’ on-the-job learning [69,70].

3.2.2. Explanatory Variables

The most commonly used indicator to characterize artificial intelligence’s impact on workers is the routine task intensity constructed by Autor and Dorn [71]. They have found that the new technological progress led by AI is task-biased rather than skill-biased. The greater degree of routine cognitive and routine manual intensity a task has, the more codable it is, the easier it is to be performed by machine learning algorithms, and the greater the impact of AI on it [72,73]. Therefore, based on the task characteristics of different occupations in the *Dictionary of Occupational Titles* of the United States Department of Labor, they measure occupations’ routine intensity from the cognitive and operational dimensions to characterize AI’s impact on workers. This indicator is calculated based on the standard occupational classification 2009 version (SOC-2009). We use the occupational crosswalk system from the United States Department of Labor to convert this index into the ISCO-2008 standard indicator, and then match it to CGSS data, denoted as AI. It is worth pointing out that in the crosswalk from SOC-2009 to ISCO-2008, a certain ISCO-2008 occupation may correspond to multiple SOC-2009 occupations. In this regard, we calculate the mean value as the AI indicator of the ISCO-2008 occupation. In addition, other measures are also used for robustness checks [25].

3.2.3. Control Variables

Referring to the literature on factors influencing on-the-job learning, e.g., [18,69], this paper comprehensively controls for variables in six aspects to avoid omitted variable bias: (1) Demographic characteristics include gender, age, and the quadratic term of age; (2) Work characteristics include personal income, whether one works in the system and whether one has pension and medical insurance; (3) Human capital characteristics include educational status and health condition; (4) Social identity characteristics include whether one belongs to an ethnic minority, whether one has religious beliefs, and whether one is a Communist Party of China (CPC) member; (5) Family characteristics include whether one is married, family size, and number of children; (6) Time and province dummies. Table 1 presents the descriptive statistics of the above variables.

Table 1. Descriptive statistics.

Variable	Description	Obs.	Mean	Std. Dev.	Min.	Max.
	Dependent Variables					
Further Learning	Frequency of on-the-job learning, 1–5 levels	12,418	1.943	1.064	1	5
Whe_Learning	Whether often participate in on-the-job learning	12,418	0.282	0.450	0	1
	Explanatory Variables					
AI	AI (unweighted index)	12,418	−0.473	1.333	−6.190	4.235
AI_weighted	AI (weighted index)	12,418	−0.474	1.348	−6.190	4.235
AI_median	AI (median index)	12,418	−0.474	1.345	−6.190	4.235
AI_max	AI (max index)	12,418	0.113	1.618	−6.190	6.100
AI_2	AI index subtracting the non-routine cognitive analytic and non-routine interpersonal intensity	12,418	−0.335	2.570	−7.407	5.887

Table 1. *Cont.*

Variable	Description	Obs.	Mean	Std. Dev.	Min.	Max.
AI_3	AI_2 index subtracting the non-routine manual physical and non-routine manual interpersonal intensity	12,262	−0.382	2.905	−7.976	6.221
AI_Frey	Another AI index constructed by Frey and Osborne [25]	12,085	0.634	0.312	0.004	0.990
Control Variables						
Demographic characteristics						
Whether female	Yes = 1, No = 0	12,418	0.471	0.499	0	1
Age	Age	12,418	45.407	13.145	18	75
Age_squared	Squared term of age	12,418	2234.583	1219.794	324	5625
Work characteristics						
ln_Income	Logarithm of personal income (RMB)	11,867	9.451	2.771	0	16.113
Whether working-in-system	Yes = 1, No = 0	12,347	0.112	0.315	0	1
Whether having pension	Yes = 1, No = 0	12,401	0.742	0.437	0	1
Whether having medical insurance	Yes = 1, No = 0	12,412	0.934	0.248	0	1
Human capital characteristics						
Whether higher educated	Yes = 1, No = 0	12,414	0.139	0.345	0	1
Whether healthy	Yes = 1, No = 0	12,414	0.633	0.482	0	1
Social identity characteristics						
Whether ethnic minorities	Yes = 1, No = 0	12,418	0.081	0.273	0	1
Whether religious believer	Yes = 1, No = 0	12,418	0.095	0.293	0	1
Whether CPC member	Yes = 1, No = 0	12,403	0.101	0.302	0	1
Family characteristics						
Whether married	Yes = 1, No = 0	12,418	0.825	0.380	0	1
Number of children	Number of children	12,418	1.515	1.035	0	10
Family size	Number of family members	12,418	2.940	1.424	1	12
Year dummies						
Province dummies						

Notes: Working in-system in China refers to having jobs in Communist Party of China organizations, governments, and state-owned corporations. Compared with out-system jobs, in-system jobs bring better social security and additional hidden benefits. Whether higher educated denotes whether the respondent has a college degree or higher.

4. Results and Discussion

4.1. Benchmark Empirical Results

First, the following ordinary least squares (OLS) model is constructed to examine the impact of AI on on-the-job learning:

$$Further_Learning_i = \alpha_0 + \alpha_1 AI_i + x'_i \psi^1 + d_y + d_r + \varepsilon_i^1 \tag{1}$$

In Model (1), the dependent variable $Further_Learning_i$ refers to employed respondent’s frequency of on-the-job learning. The explanatory variable characterizes the degree to which the respondent’s work is affected by AI. x'_i , d_y and, d_r are the vectors of control variables, as well as year and province dummy variables as mentioned above. α_0 , α_1 , and ψ^1 are parameters to be estimated; we specifically focus on α_1 .

Estimation results of Model (1) are shown in Table 2. Column (1), which does not include any control variables, indicates that the effect of artificial intelligence is significantly negatively related to on-the-job learning frequencies. Columns (2)–(7) sequentially include the six types of control variables mentioned above. Results display that no matter which

controls are included in the regression, the estimated coefficients of AI, which are -0.075 , -0.06 , -0.049 , -0.048 , -0.05 , and -0.05 , are all significantly negative at the 1% level, implying that AI significantly reduces on-the-job learning. In addition, as different aspects of characteristics are added, estimates of the relationship between AI and on-the-job learning decrease slightly but basically stabilize at around -0.050 , suggesting that the negative relationship between the two factors is robust and not interfered by other elements. The estimated results of controls are generally in line with theoretical expectations and the existing literature. For example, younger workers participate in more on-the-job learning because they have more opportunities of career development and acquire new skills more quickly [56,57]. Higher-educated employees have a greater willingness to engage in further learning [31]. Those with higher incomes can afford higher learning costs, and therefore, learn on the job more frequently.

Table 2. Impacts of AI on on-the-job learning.

Model	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS
Variable	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning
AI	-0.085^{***} (0.007)	-0.075^{***} (0.007)	-0.060^{***} (0.007)	-0.049^{***} (0.007)	-0.048^{***} (0.007)	-0.050^{***} (0.007)	-0.050^{***} (0.006)
Whether female		-0.139^{***} (0.018)	-0.065^{***} (0.018)	-0.074^{***} (0.017)	-0.052^{***} (0.017)	-0.038^{**} (0.017)	-0.042^{***} (0.016)
Age		-0.038^{***} (0.004)	-0.060^{***} (0.004)	-0.038^{***} (0.004)	-0.041^{***} (0.004)	-0.033^{***} (0.004)	-0.031^{***} (0.004)
Age_squared		0.000^{**} (0.000)	0.000^{***} (0.000)	0.000^{***} (0.000)	0.000^{***} (0.000)	0.000^{***} (0.000)	0.000^{***} (0.000)
ln_Income			0.063^{***} (0.003)	0.047^{***} (0.003)	0.044^{***} (0.003)	0.040^{***} (0.003)	0.030^{***} (0.003)
Whether working in-system			0.728^{***} (0.032)	0.481^{***} (0.032)	0.387^{***} (0.033)	0.373^{***} (0.033)	0.378^{***} (0.032)
Whether having pension			0.275^{***} (0.020)	0.184^{***} (0.019)	0.165^{***} (0.019)	0.157^{***} (0.019)	0.125^{***} (0.020)
Whether having medical insurance			0.125^{***} (0.034)	0.097^{***} (0.033)	0.080^{**} (0.033)	0.100^{***} (0.033)	0.125^{***} (0.032)
Whether higher educated				0.839^{***} (0.030)	0.736^{***} (0.031)	0.690^{***} (0.031)	0.601^{***} (0.031)
Whether healthy				0.110^{***} (0.018)	0.095^{***} (0.018)	0.092^{***} (0.017)	0.096^{***} (0.017)
Whether ethnic minorities					-0.149^{***} (0.031)	-0.131^{***} (0.030)	-0.084^{**} (0.036)
Whether religious believer					0.044 (0.030)	0.069^{**} (0.031)	0.062^{**} (0.031)
Whether CPC member					0.483^{***} (0.035)	0.483^{***} (0.034)	0.460^{***} (0.034)
Whether married						-0.004 (0.025)	-0.002 (0.025)
Number of children						-0.129^{***} (0.010)	-0.105^{***} (0.010)
Family size						-0.010 (0.006)	-0.004 (0.006)
Time dummies	No	No	No	No	No	No	Yes
Province dummies	No	No	No	No	No	No	Yes
Constant	1.902^{***} (0.010)	3.461^{***} (0.096)	2.814^{***} (0.107)	2.268^{***} (0.103)	2.410^{***} (0.103)	2.382^{***} (0.106)	2.701^{***} (0.114)
Observations	12,418	12,418	11,788	11,780	11,770	11,770	11,770
Adjusted R ²	0.011	0.138	0.239	0.298	0.315	0.327	0.351

Notes: $***$, $**$, and $*$ indicate significance at the levels of 1%, 5%, and 10%, respectively. The values in parentheses are standard errors robust to heteroskedasticity. Yes means the corresponding variables are controlled in the regression, while no means not controlled. Adjusted R² is reported for linear models and pseudo R² is reported for nonlinear models. The same applies to other tables below.

4.2. Robustness and Endogeneity Tests

4.2.1. Using Other AI Measures

In converting the artificial intelligence indicator constructed by Autor and Dorn [71] from SOC-2009 to ISCO-2008 occupations, when an ISCO-2008 occupation has more than one corresponding occupations in SOC-2009, the mean measure of SOC-2009's AI indexes is used in the benchmark analysis. However, this approach fails to take into account the scale of employment in different SOC-2009 occupations. To address this, this paper constructs a weighted average AI indicator, denoted as AI_weighted, by taking the employment scale of different occupations in the US occupational employment survey (OES) as the weight to check the robustness of the above findings. In addition, to avoid the interference of outliers to which the mean and weighted values are subject to, the median AI index of SOC-2009 occupations is also constructed for ISCO-2008, denoted as AI_median. Furthermore, to check the robustness of findings, a more radical conversion is applied, in which the maximum value of different SOC-2009 occupations' AI indicators is used.

Moreover, to more comprehensively characterize working features, considering that the higher the non-routine intensity, the lower the influence of AI on the occupation, this research subtracts the non-routine cognitive analytic and non-routine interpersonal intensities of the occupation from its routine cognitive and routine manual intensities to construct the AI_2 index. Based on this, we also calculate the AI_3 indicator that further subtracts the non-routine manual physical and non-routine manual interpersonal intensities from AI_2. Then, this paper utilizes these different AI indicators based on Autor and Dorn [71] to perform robustness tests.

In addition, we are also concerned about whether the conclusions of this paper still hold if artificial intelligence indicators constructed by other scholars are exploited. Another AI indicator newly developed by Frey and Osborne [25] has also received attention recently. So, we performed a robustness test using this indicator, denoted as AI_Frey. This indicator, based on the characteristics of different occupations in the occupational information network (O*NET), uses machine learning algorithms to measure the degree to which different occupations are affected by AI. It takes values in the interval [0, 1], with higher values indicating AI's greater impact on people. Robustness tests results using the above different AI indexes are exhibited in Table 3. It is shown that the impact of AI on on-the-job learning is significantly negative at the 1% level, regardless of which indicator is applied. Furthermore, AI's estimated coefficients obtained using the above indicators are largely consistent, confirming the robustness of the findings in this paper.

Table 3. Robustness and endogeneity tests: using other AI measures.

Model	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Variable	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning
AI_weighted	−0.049 *** (0.006)					
AI_median		−0.049 *** (0.006)				
AI_max			−0.045 *** (0.005)			
AI_2				−0.046 *** (0.004)		
AI_3					−0.034 *** (0.003)	
AI_Frey						−0.317 *** (0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.703 *** (0.114)	2.703 *** (0.114)	2.740 *** (0.114)	2.738 *** (0.113)	2.705 *** (0.114)	2.926 *** (0.117)
Observations	11,770	11,770	11,770	11,770	11,626	11,454
Adjusted R ²	0.351	0.351	0.351	0.358	0.355	0.351

4.2.2. Dealing with Measurement Errors in the On-the-Job Learning Indicator

Considering that different respondents may have varied understandings of the options presented in the questionnaire, the dependent variable may suffer from measurement errors. To check the robustness of the benchmark regression results, this paper further constructs the dummy variable *Whe_Learning*, according to whether ratings of on-the-job learning frequencies are greater than 3. Therefore, if the respondents seldom or never participate in on-the-job learning, *Whe_Learning* is coded as 0 and as 1 if otherwise. This dummy variable can mitigate measurement errors caused by differences in respondents' understandings of question options to a large extent. The reason lies in the fact that although different respondents may have divergent understandings of the frequency of "sometimes", "often", and "frequently", there is hardly any difference in the judgment of whether the further learning frequency belongs to *Whe_Learning* = 0 (never or seldom) or *Whe_Learning* = 1 (sometimes, often or frequently). Since this explained variable is a binary variable, the predicted values of the OLS model may be outside [0, 1], so probit and logit models based on the maximum likelihood estimation are applied. The log-likelihood function is of the following form:

$$\ln L = \sum_{i \in S} \ln \left[F \left(\beta_0 + \beta_1 AI_i + \mathbf{x}'_i \boldsymbol{\psi}^2 + d_y + d_r \right) \right] + \sum_{i \notin S} \ln \left[1 - F \left(\beta_0 + \beta_1 AI_i + \mathbf{x}'_i \boldsymbol{\psi}^2 + d_y + d_r \right) \right] \quad (2)$$

$$F(\cdot) = \Phi \left(\beta_0 + \beta_1 AI_i + \mathbf{x}'_i \boldsymbol{\psi}^2 + d_y + d_r \right) \quad (3)$$

or

$$F(\cdot) = \exp \left(\beta_0 + \beta_1 AI_i + \mathbf{x}'_i \boldsymbol{\psi}^2 + d_y + d_r \right) / \left\{ 1 + \exp \left(\beta_0 + \beta_1 AI_i + \mathbf{x}'_i \boldsymbol{\psi}^2 + d_y + d_r \right) \right\} \quad (4)$$

In expression (2), *S* is the set of all observations such that *Whe_Learning_i* = 1. *F*(·) can take the form of either Equation (3) or Equation (4). Equation (3), where $\Phi(\cdot)$ is the standard normal cumulative density function, corresponds to the probit model. Equation (4) is applied to the logit model. Based on this, β_1 and $\boldsymbol{\psi}^2$ are estimated by $\max_{\beta_1, \boldsymbol{\psi}^2} \ln L$.

The results estimated using the probit model and logit model are shown in Tables 4 and 5, respectively. Similarly, by stepwise adding control variables in six aspects, the estimated coefficients of AI's effect on *Whe_Learning* remain significantly negative at the 1% level. This demonstrates that AI significantly inhibits on-the-job learning after dealing with measurement errors in the on-the-job learning indicator, no matter whether a probit or logit model is employed.

Table 4. Robustness and endogeneity tests: using the dummy measure of on-the-job learning (probit model).

Model	(1) Probit	(2) Probit	(3) Probit	(4) Probit	(5) Probit	(6) Probit	(7) Probit
Variable	Whe_Learning	Whe_Learning	Whe_Learning	Whe_Learning	Whe_Learning	Whe_Learning	Whe_Learning
AI	−0.095 *** (0.009)	−0.086 *** (0.009)	−0.074 *** (0.010)	−0.064 *** (0.010)	−0.064 *** (0.010)	−0.068 *** (0.010)	−0.067 *** (0.010)
Demographic characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Work characteristics	No	No	Yes	Yes	Yes	Yes	Yes
Human capital characteristics	No	No	No	Yes	Yes	Yes	Yes
Social identity characteristics	No	No	No	No	Yes	Yes	Yes
Family characteristics	No	No	No	No	No	Yes	Yes
Time and province characteristics	No	No	No	No	No	No	Yes

Table 4. Cont.

Model	(1) Probit	(2) Probit	(3) Probit	(4) Probit	(5) Probit	(6) Probit	(7) Probit
Variable	Whe_ Learning	Whe_ Learning	Whe_ Learning	Whe_ Learning	Whe_ Learning	Whe_ Learning	Whe_ Learning
Constant	−0.627 *** (0.013)	0.722 *** (0.140)	0.029 (0.170)	−0.477 *** (0.166)	−0.313 * (0.167)	−0.393 ** (0.179)	−0.002 (0.193)
Observations	12,418	12,418	11,788	11,780	11,770	11,770	11,770
Pseudo R ²	0.008	0.087	0.161	0.200	0.213	0.223	0.243

Table 5. Robustness and endogeneity tests: using the dummy measure of on-the-job learning (logit model).

Model	(1) Logit	(2) Logit	(3) Logit	(4) Logit	(5) Logit	(6) Logit	(7) Logit
Variable	Whe_ Learning	Whe_ Learning	Whe_ Learning	Whe_ Learning	Whe_ Learning	Whe_ Learning	Whe_ Learning
AI	−0.161 *** (0.016)	−0.144 *** (0.016)	−0.123 *** (0.017)	−0.109 *** (0.017)	−0.109 *** (0.017)	−0.117 *** (0.017)	−0.116 *** (0.018)
Demographic characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Work characteristics	No	No	Yes	Yes	Yes	Yes	Yes
Human capital characteristics	No	No	No	Yes	Yes	Yes	Yes
Social identity characteristics	No	No	No	No	Yes	Yes	Yes
Family characteristics	No	No	No	No	No	Yes	Yes
Time and province characteristics	No	No	No	No	No	No	Yes
Constant	−1.021 *** (0.022)	0.938 *** (0.241)	−0.377 (0.331)	−1.000 *** (0.299)	−0.702 ** (0.298)	−0.931 *** (0.319)	−0.285 (0.342)
Observations	12,418	12,418	11,788	11,780	11,770	11,770	11,770
Pseudo R ²	0.008	0.087	0.162	0.199	0.213	0.223	0.242

4.2.3. Using Ordered Response Models

The dependent variable $Further_Learning_i$ is an ordered variable because it takes the values of 1, 2, 3, 4, and 5. This means that although further learning frequencies are ordered from “never” to “frequently”, the spacing between the values of $Further_Learning_i$ may not be the same across different levels. The linear models, such as OLS, assume that these categories are equally spaced, which may not be the case. Therefore, to check the robustness of the conclusions obtained from the linear model, ordered response models are further applied, which assume that the explained variable is ordinal and different categories are not equally spaced. Specifically, based on $Further_Learning_i$ the sample is divided into five subgroups, denoted $g = 1$ to 5, representing those that never, seldom, sometimes, often, and frequently engage in on-the-job learning, respectively. The probability p_{gi} of a given observation i in group g is

$$p_{gi} = Pr(Further_Learning_i = g) = Pr(\chi_{g-1} < \gamma_0 + \gamma_1 AI_i + \mathbf{x}'_i \boldsymbol{\psi}^3 + d_y + d_r + \epsilon_i \leq \chi_g) \quad (5)$$

$$Pr(\cdot) = \Phi(\chi_g - \gamma_0 - \gamma_1 AI_i - \mathbf{x}'_i \boldsymbol{\psi}^3 - d_y - d_r) - \Phi(\chi_{g-1} - \gamma_0 - \gamma_1 AI_i - \mathbf{x}'_i \boldsymbol{\psi}^3 - d_y - d_r) \quad (6)$$

or

$$Pr(\cdot) = 1 / \{1 + \exp(\gamma_0 + \gamma_1 AI_i + \mathbf{x}'_i \boldsymbol{\psi}^3 + d_y + d_r - \chi_g)\} - 1 / \{1 + \exp(\gamma_0 + \gamma_1 AI_i + \mathbf{x}'_i \boldsymbol{\psi}^3 + d_y + d_r - \chi_{g-1})\} \quad (7)$$

In Equation (5), χ_0 is $-\infty$ and χ_5 is $+\infty$. $Pr(\cdot)$ can take two forms. The first is to use Equation (6) for an ordered probit model estimation, where $\Phi(\cdot)$ is the standard normal cumulative distribution function. The other approach is to apply Equation (7) for an ordered logit model estimation. Accordingly, the log likelihood of the maximum likelihood estimation (MLE) is

$$lnL = \sum_{i=1}^N \sum_{g=1}^5 I_g(Further_Learning_i) ln p_{gi} \tag{8}$$

where $I_g(Further_Learning_i) = \begin{cases} 1, & \text{if } Further_Learning_i = g \\ 0, & \text{if } Further_Learning_i \neq g \end{cases}$ and N is the sample size.

Based on this, γ_1 and ψ^3 are estimated by $\max_{\gamma_1, \psi^3} lnL$.

The estimation results obtained from the ordered probit and ordered logit models are displayed in Tables 6 and 7, respectively. In all regressions, the estimated coefficients of artificial intelligence’s impact on $Further_Learning_i$ are significantly negative at the 1% level, consistent with the conclusions derived from the benchmark regressions. This indicates that the application of AI decreases workers’ further learning. Additionally, with the inclusion of different control variables, the estimated coefficients of AI are stable around -0.06 , suggesting that the conclusions of this paper are robust and that AI’s effects on on-the-job learning are not altered by model selection or the inclusion of other factors.

Table 6. Robustness and endogeneity tests: using ordered response models (ordered probit model).

Model	(1) Oprobit	(2) Oprobit	(3) Oprobit	(4) Oprobit	(5) Oprobit	(6) Oprobit	(7) Oprobit
Variable	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning
AI	−0.085 *** (0.007)	−0.077 *** (0.008)	−0.065 *** (0.008)	−0.055 *** (0.008)	−0.055 *** (0.008)	−0.060 *** (0.008)	−0.060 *** (0.008)
Demographic characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Work characteristics	No	No	Yes	Yes	Yes	Yes	Yes
Human capital characteristics	No	No	No	Yes	Yes	Yes	Yes
Social identity characteristics	No	No	No	No	Yes	Yes	Yes
Family characteristics	No	No	No	No	No	Yes	Yes
Time and province characteristics	No	No	No	No	No	No	Yes
Observations	12,418	12,418	11,788	11,780	11,770	11,770	11,770
Pseudo R ²	0.004	0.063	0.109	0.129	0.138	0.145	0.161

Table 7. Robustness and endogeneity tests: using ordered response models (ordered logit model).

Model	(1) Ologit	(2) Ologit	(3) Ologit	(4) Ologit	(5) Ologit	(6) Ologit	(7) Ologit
Variable	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning
AI	−0.140 *** (0.013)	−0.128 *** (0.013)	−0.110 *** (0.013)	−0.094 *** (0.013)	−0.094 *** (0.013)	−0.101 *** (0.014)	−0.103 *** (0.014)
Demographic characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Work characteristics	No	No	Yes	Yes	Yes	Yes	Yes
Human capital characteristics	No	No	No	Yes	Yes	Yes	Yes
Social identity characteristics	No	No	No	No	Yes	Yes	Yes
Family characteristics	No	No	No	No	No	Yes	Yes

Table 7. Cont.

Model	(1) Ologit	(2) Ologit	(3) Ologit	(4) Ologit	(5) Ologit	(6) Ologit	(7) Ologit
Variable	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning
Time and province characteristics	No	No	No	No	No	No	Yes
Observations	12,418	12,418	11,788	11,780	11,770	11,770	11,770
Pseudo R ²	0.004	0.067	0.113	0.134	0.143	0.150	0.166

4.2.4. Instrumental Variable Methods

In benchmark regressions, the impact of artificial intelligence on on-the-job learning may be subject to the endogeneity problem for two reasons. On the one hand, the reverse causality problem may arise from the concern that workers who learn more frequently may be less likely to be replaced by AI because of their high human capital, and thus, AI has less impact on the jobs they perform. On the other hand, there may exist other unobserved factors that could affect on-the-job learning in the random disturbance term, resulting in biased estimates of AI's coefficient. To address potential endogeneity issues, the following two-stage least squares (2SLS) model is constructed:

$$AI_i = \delta_0 + \delta_1 RII_i + \mathbf{x}'_i \boldsymbol{\psi}^4 + d_y + d_r + \varepsilon_i^4 \quad (9)$$

$$\text{Further_Learning}_i = \eta_0 + \eta_1 \hat{AI}_i + \mathbf{x}'_i \boldsymbol{\psi}^5 + d_y + d_r + \varepsilon_i^5 \quad (10)$$

In Model (9), RII_i is the instrumental variable. This is the first stage regression of 2SLS, in which RII_i is used to estimate AI_i . In Model (10), the predicted value of AI_i is used to test its effect on on-the-job learning. The instrumental variable RII_i is the routine intensity index constructed by Marcolin et al. [74]. The higher the RII_i , the higher the routine intensity of the occupation, and the easier it is to be influenced by artificial intelligence [74]. Therefore, this instrumental variable satisfies the correlation prerequisite. In addition, this indicator also satisfies exogeneity due to the following two reasons. First, from a reverse causality perspective, RII_i is an indicator measured based on the 2011–2012 OECD survey of adult skills, whereas the data used in this paper are from the 2017–2018 CGSS, making it unlikely that Chinese respondents in 2017 and 2018 reversely affect the earlier RII_i . Second, RII_i is an indicator at the sectoral level, which is based on three-digit ISCO-2008, whereas AI_i is an individual-level four-digit ISCO2008 measure. Consequently, RII_i is exogenous to respondents' individual characteristics. Based on the above two points, RII_i satisfies the exogeneity condition of instrumental variables. Column (1) of Table 8 exhibits the estimation results of the first stage of 2SLS, indicating that RII_i significantly increases AI_i at the 1% level, proving the above proposition. Additionally, the F value of this regression is 74.127, much larger than the empirical criterion of 10, confirming that this instrumental variable is valid for the estimation. The results of the second-stage regression of 2SLS are listed in Column (2) of Table 8. After addressing endogeneity, the effect of AI on on-the-job learning is still significantly negative at the 1% level, demonstrating that AI robustly inhibits on-the-job learning. Furthermore, as presented in Columns (3)–(5) of Table 8, when employing different instrumental variable models, including the limited information maximum likelihood estimation (LIML), two-step optimal generalized method of moments (GMM) and iterative GMM (IGMM), AI's impact on on-the-job learning remains significantly negative at the 1% level. This supports the notion that the findings of this paper are not affected by the endogeneity issue and are highly reliable.

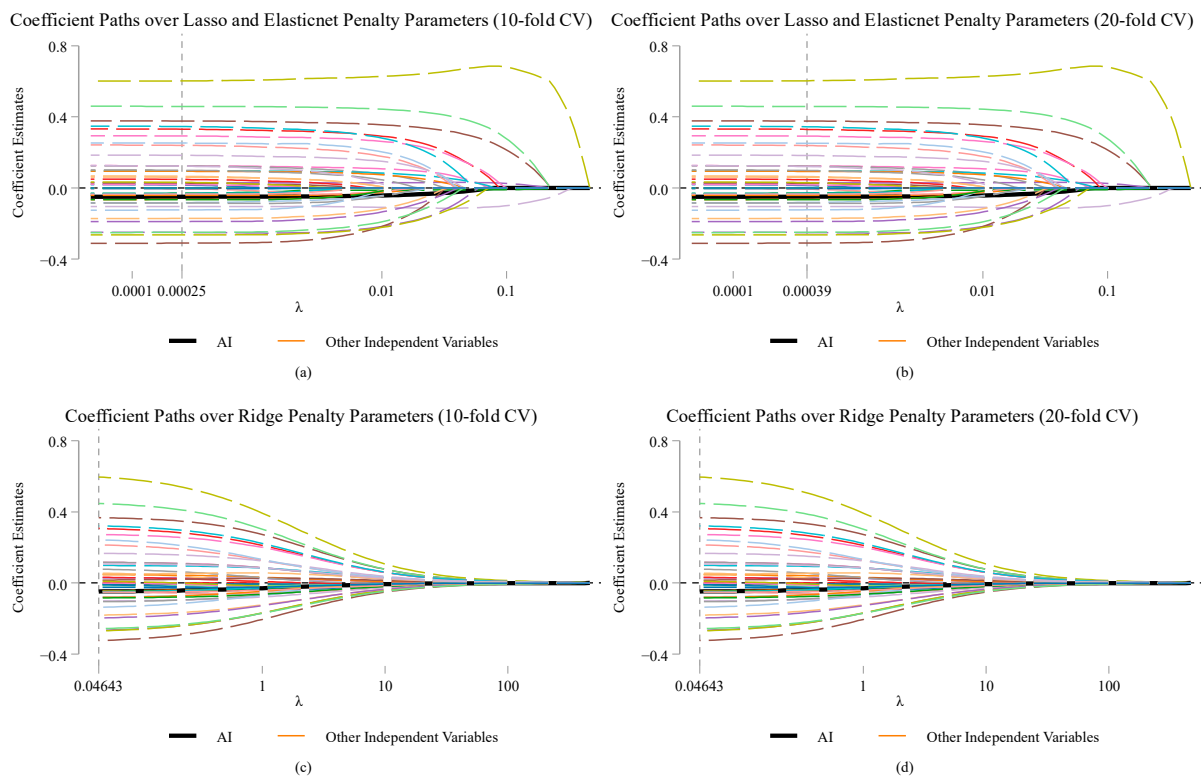


Figure 2. Coefficient paths in penalized machine learning estimations.

4.2.6. Placebo Tests

We have examined the impact of artificial intelligence on on-the-job learning from different perspectives, but there is still a concern that the statistical significance of AI's estimates may be due to uncontrolled random factors. If this speculation is true, the results of this paper would not be valid. To address this concern, placebo tests were conducted. Specifically, we randomly assigned the AI indicator in the sample 1000 times to obtain the placebo explanatory variable $AI_placebo_i$, and then used these 1000 new samples for regression to estimate the impact of $AI_placebo_i$ on on-the-job learning. The estimated results are plotted in Figure 3, where the six sub-figures are the placebo test results performing the benchmark regressions in Columns (2)–(7) of Table 2, with the stepwise addition of control variables. The black solid lines are the probability density curves of $AI_placebo_i$'s estimated coefficients in regressions with the 1000 new samples. The colored scatters are the P values corresponding to the estimates of $AI_placebo_i$. The red vertical dashed lines signify the estimates of benchmark regressions in Columns (2)–(7) of Table 2. It is clear that the distributions of $AI_placebo_i$'s coefficients are all basically centered on 0, showing a near-normal distribution in all regression models. The colored scatters, which are the P values corresponding to the estimated coefficients of $AI_placebo_i$, are almost all higher than 0.1. More importantly, the estimated coefficients of benchmark regressions in Columns (2)–(7) of Table 2 are all much smaller than the 1000 placebo estimates. This proves that the magnitude of the relationship between AI and on-the-job learning owing to chance factors is far from the results obtained in benchmark regressions. Therefore, this provides evidence that the effect of AI on further learning is not due to uncontrolled random factors.

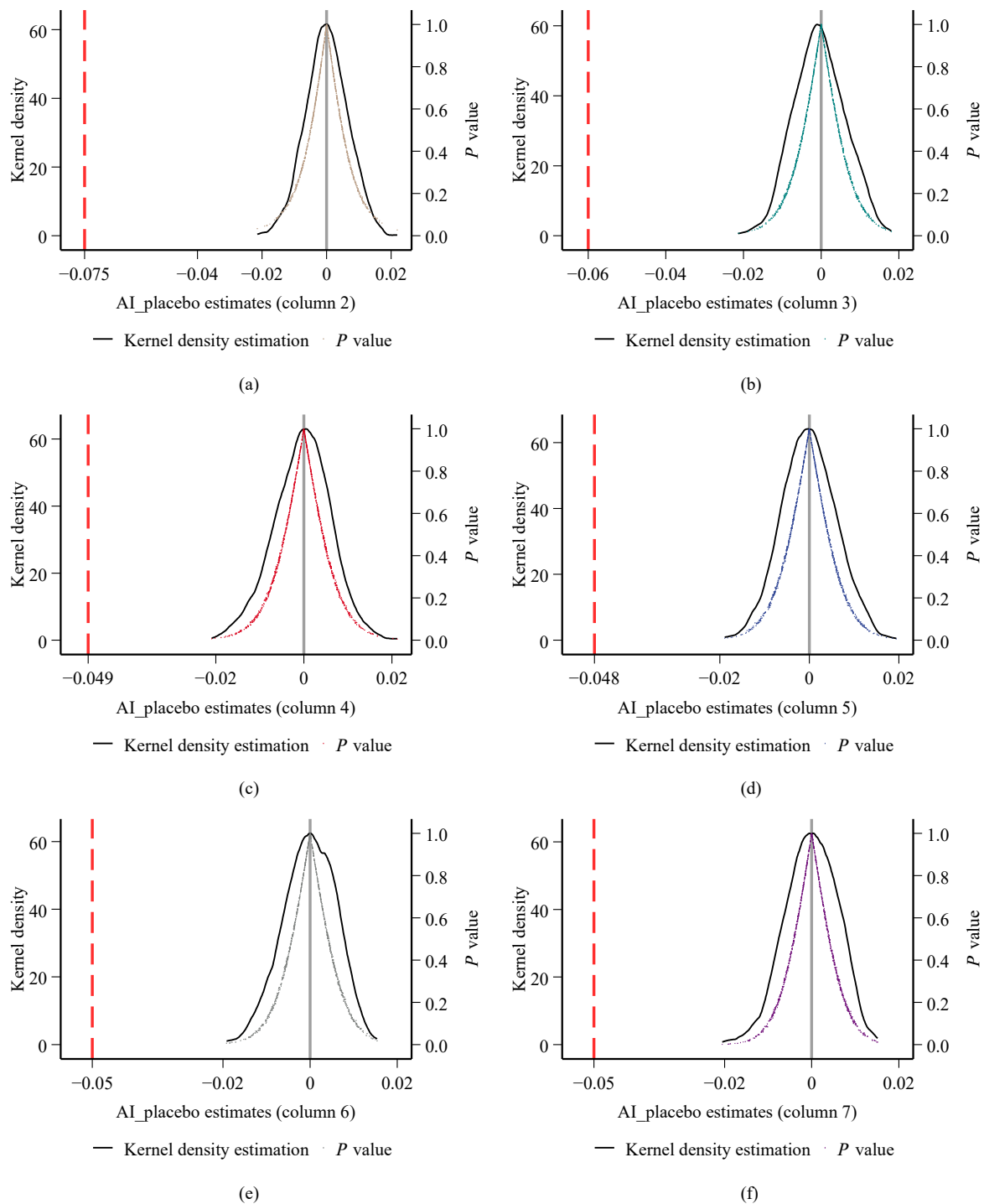


Figure 3. Placebo tests results. Notes: Sub-figures (a–f) depict kernel density curves of *AI placebo*'s estimated coefficients and the corresponding *p* values in regressions of Columns (2)–(7) of Table 2, respectively.

5. Mechanism Analysis

The preceding sections have confirmed the negative effect of artificial intelligence on on-the-job learning. We next examine the mechanisms by which AI influences workers' on-the-job learning. Based on the above theoretical analysis, this paper further tests the future expectation mechanism, income mechanism, and working-time mechanism. Referring to Alesina et al. [75], the following model is constructed to conduct the mechanism analysis based on dealing with endogeneity:

$$Mediator_i = \theta_0 + \theta_1 \hat{AI}_i + \mathbf{x}'_i \boldsymbol{\psi}^6 + d_y + d_r + \varepsilon_i^6 \tag{11}$$

$$Further_Learning_i = \lambda_0 + \lambda_1 \hat{AI}_i + \lambda_2 Mediator_i + \mathbf{x}'_i \boldsymbol{\psi}^7 + d_y + d_r + \varepsilon_i^7 \tag{12}$$

where $Mediator_i$ is the mediating variable. \hat{AI}_i is the fitted value of AI in the first stage regression of 2SLS in Model (9). Models (11) and (12) use the fitted values of AI obtained from Model (9) for the second stage regression of 2SLS. If both θ_1 in Model (11) and λ_2 in Model (12) are estimated to be significant, $Mediator_i$ is proven to mediate AI's effect on on-the-job learning.

5.1. Future Expectation Mechanism

In the first part of theoretical analysis, two hypotheses concerning the future expectation mechanism (H1a and H1b) are proposed. It has been discussed that the pessimistic expectations caused by AI may produce a stimulation effect and thus promote on-the-job learning. At the same time, the pessimistic expectations can also bring a burnout effect, which may inhibit further learning. In light of this, this paper tests the future expectation mechanism using the above mechanism test approach. To directly measure people's future expectations, we construct a variable *Optimism about future*, based on respondents' answers to the CGSS question "I am optimistic about my future". This variable, based on the five-point Likert scale, classifies the level of agreement to the above question from 1–5 in the order of "strongly disagree", "disagree", "neither agree nor disagree", "agree", and "strongly agree". Obviously, higher scores represent more optimistic future expectations. Because this question comes from the extension module of the CGSS questionnaire in the 2017 wave, the number of observations in regressions with this variable is smaller. Additionally, a variable indirectly characterizing future expectations, *Anticipated social status*, is utilized, which is based on the question "what social class do you think you will belong to in the next 10 years?" The options for this question are on a scale from 1 to 10, with 10 representing the top social class and 1 being the bottom class. Based on the above two variables that directly and indirectly measure workers' future expectations, this paper conducts the following mechanism analysis.

Table 10 shows the test results of the future expectation mechanism. In Columns (2) and (4), artificial intelligence significantly decreases people's expectations for the future. Meanwhile, the results in Columns (3) and (5) indicate that the more optimistic towards future workers are and the higher the expected social status, the larger the further learning frequencies. Moreover, the absolute values of AI's estimated coefficients drop from 0.227 to 0.211 when the mediating variable is included in the regression. This implies that AI reduces on-the-job learning frequencies by lowering workers' future expectations. Therefore, H1b is confirmed, meaning that more pessimistic expectations caused by AI inhibit people's on-the-job learning.

Table 10. Future expectation mechanism analysis.

Model	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS
Variable	Further Learning	Optimism about Future	Further Learning	Anticipated Social Status	Further Learning
AI	−0.227 *** (0.017)	−0.075 ** (0.030)	−0.211 *** (0.044)	−0.279 *** (0.033)	−0.211 *** (0.017)
Optimism about future			0.080 *** (0.029)		
Anticipated social status					0.056 *** (0.005)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	2.776 *** (0.117)	3.937 *** (0.242)	2.130 *** (0.327)	6.636 *** (0.239)	2.420 *** (0.123)
Observations	11,770	1864	1864	11,253	11,253
Adjusted R ²	0.302	0.045	0.287	0.129	0.321

5.2. Economic Income Mechanism

In addition to the future expectation mechanism, artificial intelligence may also influence on-the-job learning through its impact on income. In this regard, H2a and H2b are put forward in the second part of the theoretical analysis. It is shown that the complementarity and cost-saving effects of AI may increase income, and therefore, promote on-the-job learning. However, its replacement and mismatch effects can reduce earnings, which may inhibit further learning. To test the hypotheses, this paper firstly uses workers' personal income for mechanism analysis. The results in Column (2) of Table 11 demonstrate that AI significantly reduces workers' personal income at the 1% level. In Column (3), personal income significantly increases the frequency of on-the-job learning. Moreover, after controlling for income, the absolute value of AI's estimated coefficient decreases from 0.230 to 0.227, while still being significant at the 1% level, compared with that in Column (1). This means that personal income mediates the negative effect of AI on on-the-job learning. Therefore, H2b is supported. Furthermore, we perform a robustness test for this mechanism using household income. To avoid multicollinearity, personal income is not controlled in Columns (4) and (5). The results show that the economic income mechanism still holds when household income is used as the mediating variable. Therefore, by cutting down people's income, AI decreases the financial resources they can spend on human capital investment, thus reducing on-the-job learning.

Table 11. Economic income mechanism analysis.

Model	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS
Variable	Further Learning	Personal Income	Further Learning	Family Income	Further Learning
AI	−0.230 *** (0.017)	−0.125 *** (0.036)	−0.227 *** (0.017)	−0.136 *** (0.022)	−0.217 *** (0.018)
Personal Income			0.023 *** (0.003)		
Family Income					0.057 *** (0.006)
Other controls	Yes	Yes	Yes	Yes	Yes
Constant	2.956 *** (0.113)	7.714 *** (0.342)	2.776 *** (0.117)	10.142 *** (0.201)	2.426 *** (0.135)
Observations	11,770	11,770	11,770	11,356	11,356
Adjusted R ²	0.298	0.227	0.302	0.302	0.308

Notes: other controls in this table refer to control variables excluding ln_Income.

5.3. Working Time Mechanism

On-the-job learning involves not only financial costs but also investment in time. In this respect, H3a and H3b are proposed in theoretical analysis. On the one hand, the deskilling effect of artificial intelligence increases working time, and thus, may inhibit on-the-job learning. However, on the other hand, its productivity and replacement effect can reduce working time, which may enhance on-the-job learning. To test the mechanism, the number of hours worked per week is firstly used as the mediator for analysis. Results in Column (2) of Table 12 exhibit that AI significantly increases working hours at the 1% level. This indicates that the application of AI does not reduce workers' workload, while extending their working time because of its deskilling effect as discussed in the theoretical analysis, which is consistent with the existing literature [22,48,49]. In Column (3), working hours significantly reduce people's further learning, demonstrating that the longer the working time, the less time they can spend on learning. Furthermore, the absolute value of AI's estimated coefficient in Column (3), which is 0.220, drops compared to 0.227 in Column (1). This implies that AI inhibits on-the-job learning through increasing working hours, proving H3a. Furthermore, to test the robustness of this mechanism, a dummy variable of whether one overworks is generated. Referring to [76,77], working more than 50 h per week is defined as overworking. Since the explained variable here is a binary variable, the IV Probit model is applied for estimation. As illustrated in Columns (4) and

(5), AI also discourages further learning by increasing the probability of overworking, again verifying H3a. Therefore, it is concluded that the application of AI results in longer working hours, and thus, inhibits on-the-job learning.

Table 12. Working time mechanism analysis.

Model	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) IV Probit	(5) 2SLS
Variable	Further Learning	Working Hours	Further Learning	Whether Overwork	Further Learning
AI	−0.227 *** (0.017)	3.087 *** (0.312)	−0.220 *** (0.017)	0.155 *** (0.021)	−0.210 *** (0.017)
Working hours			−0.003 *** (0.000)		
Whether overwork					−0.152 *** (0.018)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	2.776 *** (0.117)	21.161 *** (2.732)	2.820 *** (0.117)	−1.531 *** (0.168)	2.755 *** (0.117)
Observations	11,770	11,673	11,673	11,673	11,673
Adjusted R ²	0.302	0.070	0.309	.	0.310

6. Heterogeneity Analysis

6.1. Heterogeneities in Terms of Demographic Characteristics

Artificial intelligence has significantly negative effects on on-the-job learning, but this consequence may vary with different workers’ characteristics. So, we perform subgroup regressions to test heterogeneities in terms of different demographic characteristics. Results in Columns (1) and (2) of Table 13 show that AI’s negative impacts on further learning are greater for workers over 45 years of age. This may be attributed to the fact that older people have more difficulty in acquiring new skills and are less willing to learn further [55]. Consequently, faced with the new AI technology, they have lower on-the-job learning frequencies. In terms of gender, findings demonstrate that AI’s inhibitory effect on on-the-job learning is more salient for female workers. This may be because women are at a disadvantaged position in the labor market [59] and it is harder for them to switch jobs by updating skills when being displaced by new technologies. In addition, women may tend to perform routine tasks more often than men even within the same occupational category, making them more at risk of being substituted [58]. Hence, AI negatively affects their on-the-job learning to a greater extent. In addition, with respect to educational attainment, Columns (5) and (6) display that AI causes a greater reduction in on-the-job learning for workers with lower education levels. By contrast, since highly educated workers who have a college degree or higher are more competitive in the labor market, they are less affected by technological shocks [25,60]. Moreover, because employers tend to provide those who are higher educated with more training opportunities, they are easier to engage in further learning [31]. Thus, AI has a less negative impact on on-the-job learning for highly educated workers.

Table 13. Heterogeneities in terms of demographic characteristics (2SLS).

Sample	(1) Older than 45	(2) Younger than 45	(3) Men	(4) Women	(5) Lower Education Levels	(6) Higher Education Levels
Variable	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning
AI	−0.258 *** (0.032)	−0.206 *** (0.020)	−0.219 *** (0.023)	−0.240 *** (0.027)	−0.225 *** (0.019)	−0.192 *** (0.039)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.655 *** (0.100)	2.017 *** (0.094)	2.350 *** (0.163)	3.151 *** (0.165)	2.930 *** (0.128)	3.255 *** (0.435)
Observations	6001	5769	6269	5501	10,162	1608
Adjusted R ²	0.234	0.237	0.267	0.351	0.173	0.023

6.2. Heterogeneities in Terms of Working Characteristics

We have examined the variations in artificial intelligence's effect on on-the-job learning from the perspective of demographic characteristics. Next, the heterogeneities of AI's impact on workers' on-the-job learning in terms of working characteristics are explored. In detail, we conducted analysis from the three aspects of labor contract, job autonomy, and work experience. First, considering that labor contract provides the legal basis for employees to protect their rights, we performed the subsample regressions based on whether one has a labor contract. The results are reported in Columns (1) and (2) of Table 14, where the effect of AI on further learning is greater for workers without a labor contract. This indicates that strengthening labor protection through labor contracts can mitigate AI's negative effect on on-the-job learning. This echoes the findings of Li and Freeman [61] and Zhao and Tang [62] that labor contracts help improve the welfare of vulnerable workers. Second, with regard to job autonomy, according to respondents' answers to the CGSS question, "In your current job, how much autonomy do you have to decide your work pattern?", the sample is divided into lower and higher job autonomy subgroups. Specifically, the workers reporting "having no autonomy" and "having little autonomy" are classified in the lower autonomy group, while those answering "have full autonomy" and "have some autonomy" are categorized as in higher autonomy jobs. Columns (3) and (4) of Table 14 present that the inhibitory effect of AI on on-the-job learning is more prominent for workers in low-autonomy jobs. On the contrary, those with more job autonomy are less affected by AI, since they can spare more time on further learning. This also supports the previous analysis on the working-time mechanism from another angle. Third, in terms of work experience, it is generally believed that the more the working years, the more work experience is accumulated. So, based on the average working time in the current job of respondents in the CGSS sample, which is 6.120 years, we classify respondents into subgroups with less and more working experience. The results in Columns (5) and (6) show that AI has a greater impact on further learning for workers with less work experience. This can be explained by the fact that work experience can enhance employability [66].

Table 14. Heterogeneities in terms of working characteristics (2SLS).

Sample	(1) Not Having Labor Contracts	(2) Having Labor Contracts	(3) Lower Autonomy	(4) Higher Autonomy	(5) Less Working Experience	(6) More Working Experience
Variable	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning
AI	−0.276 *** (0.032)	−0.192 *** (0.021)	−0.291 *** (0.034)	−0.220 *** (0.025)	−0.228 *** (0.022)	−0.212 *** (0.029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.822 *** (0.186)	2.136 *** (0.211)	2.913 *** (0.273)	2.747 *** (0.133)	3.112 *** (0.129)	0.669 (0.454)
Observations	6790	4919	2300	9455	8605	2816
Adjusted R ²	0.235	0.154	0.235	0.314	0.339	0.166

6.3. Regional Heterogeneities

This paper further investigates the regional variations in the impact of artificial intelligence. First, we carry out an analysis from the perspective of human–AI competition. Considering that more technologically developed regions have a wider application of AI and the human–AI competition there is more intense, subsample analysis is carried out from the perspective of regional variations in technological development. Specifically, according to the median of the proportion of high-technology industry output (=high-technology industry output/GDP) in the *China Torch Statistical Yearbook 2017*, provinces are divided into high-technology and low-technology regions. The results in Table 15, Columns (1) and (2) show that AI has a greater negative effect on on-the-job learning for

workers in high-technology regions, indicating that intense human–AI competition reduces workers’ willingness to learn further to a greater extent. Moreover, this paper investigates AI’s heterogeneous effects in regions with different numbers of labor disputes and unemployment rates. Based on the median number of labor disputes and unemployment rate in the *China Labor Statistics Yearbook 2017*, provinces are divided into areas with fewer and more disputes, as well as lower and higher unemployment rates. Results demonstrate that the negative effect of AI on on-the-job learning is more pronounced in regions with more labor disputes and higher unemployment rates. This may be due to the fact that in regions with stronger labor protection, workers tend to have a more positive attitude toward new technology. They are also more likely to adapt to rapidly evolving skill demands through reeducation and retraining [68]. Therefore, more harmonious labor relations and better job security contribute to weakening AI’s adverse consequences.

Table 15. Regional heterogeneities (2SLS).

Sample	(1) Low-Technology Regions	(2) High- Technology Regions	(3) Regions with Fewer Labor Disputes	(4) Regions with More Labor Disputes	(5) Regions with Lower Unemployment Rate	(6) Regions with Higher Unemployment Rate
Variable	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning	Further Learning
AI	−0.161 *** (0.035)	−0.244 *** (0.020)	−0.162 *** (0.034)	−0.244 *** (0.020)	−0.222 *** (0.025)	−0.233 *** (0.024)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.667 *** (0.182)	2.614 *** (0.144)	2.375 *** (0.193)	2.774 *** (0.141)	2.587 *** (0.190)	2.727 *** (0.160)
Observations	4110	7660	3857	7913	5569	6201
Adjusted R ²	0.307	0.284	0.295	0.302	0.308	0.297

7. Conclusions and Implications

This paper systematically explores the impact of artificial intelligence on on-the-job learning. Based on the literature review and theoretical analysis, six hypotheses are proposed relating to three aspects of AI’s consequences on workers’ further learning. On this basis, empirical tests using CGSS data are performed. The findings demonstrate that: First, the application of AI in the workplace significantly inhibits workers’ on-the-job learning. This conclusion holds in a series of robustness and endogeneity checks, including using different AI and on-the-job learning measures, ordered response models, instrumental variable approach, penalized regressions, placebo tests, etc. Second, AI’s adverse impact on on-the-job learning is mediated by future expectation, economic income and working-time mechanisms. To be specific, AI makes people more pessimistic about their future, leading to burnout, and thus, less motivation for on-the-job learning. At the same time, AI decreases workers’ income and lengthens working hours, for which their available financial resources and disposable time for further learning are cut down, thus inhibiting on-the-job learning. Third, this paper explores the variations in AI’s impact in the aspects of demographic, working, and regional characteristics. It has been found that AI has greater negative impacts on on-the-job learning for older, female, and less-educated employees. Moreover, its effect is more conspicuous for those without a labor contract, as well as with less job autonomy and work experience. In terms of regional heterogeneities, results show that in regions with more intense human–AI competition, more labor-management conflicts, and poorer labor protection, the negative effect of AI on on-the-job learning is more pronounced. This highlights that harmonious labor relations and better employment protection are conducive to mitigating AI’s adverse impact on on-the-job learning.

In the current context of the fourth technological revolution driving the intelligent transformation, the findings of this paper have important implications for enterprises to better understand employee preferences and behaviors, and accordingly optimize their

management strategy in the era of AI. First, managers should attach great importance to AI's negative effect on employees' on-the-job learning. The findings of this paper reveal that AI does not necessarily stimulate employees to further improve their skills and increase human capital investment, but rather makes them more pessimistic about the future and thus discourages on-the-job learning. This is not favorable in terms of promoting employees to acquire new skills to achieve human–AI teaming and cooperation, and thus, is detrimental to future innovation. So, in the process of taking advantage of AI for technological upgrades, on the one hand, enterprises should bolster workers' positive psychological expectations and motivate them to improve their skills. On the other hand, more training opportunities should be provided for workers to master new skills that are compatible with the new technology, which can help enhance their human capital and foster long-term innovation. Second, enterprises should be aware of AI's adverse impact on employees' income and working time. It has been shown that AI reduces workers' income while extending work hours through its deskilling effect, leading them to have less money and time available on on-the-job learning. For this reason, for enterprises aiming to motivate employees to learn new skills, they can consider offering subsidies for skill training. At the same time, for those who have further learning motivations, managers need to optimize their working time arrangement to better support them to participate in on-the-job learning. Third, more attention should be paid to employees who have fewer learning opportunities or are less willing to learn, such as older, female and less-educated workers, as well as those with less job autonomy and work experience. It is more critical for companies to provide more training opportunities for them. Fourth, in the process of applying AI technology, governments and relevant public agencies should strengthen labor protection for workers. Measures such as improving employment contracting systems, setting up efficient labor dispute resolution mechanisms and providing better job security should be emphasized to help workers develop more stable and positive employment expectations, thus mitigating the negative effects of AI on on-the-job learning.

However, there are limitations in this study. Although this paper takes an empirical approach to examine workers' reactions to AI, it fails to analyze the personnel failure, as well as workers' reliability in human–AI teaming, resulting in a lack of an in-depth examination of on-the-job learning contents. In the future, using human reliability analysis [78,79] to evaluate the causes and impact of human error so as to study the contents of on-the-job learning would be a valuable research direction.

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