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The impact of organizational adoption of Artificial Intelligence on employees' learning behavior

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Abstract. With the continuous development of AI, Artificial Intelligence technology is gradually being introduced into workplaces. However, the impact of AI technology on employees and how employees respond to AI have not been fully researched. This study collected 303 samples through a questionnaire survey, and the empirical results indicate: (1) organizational adoption of Artificial Intelligence positively influences employees' self-directed learning behaviors; (2) job insecurity and job crafting play a chain mediating role between AI adoption and self-directed learning behaviors; (3) proactive personality positively moderates the relationship between job insecurity and job crafting.

Keywords: Artificial Intelligence adoption, job insecurity, job crafting, learning behavior

1. Introduction

With the revolutionary development of next-generation intelligent technologies such as ChatGPT, Deepseek, and Yushu Robots, the application of Artificial Intelligence in the workplace has significantly enhanced employees' decision-making effectiveness and work efficiency. Its automation process optimization capability has effectively reduced operational costs and human resource consumption for enterprises [1]. As the potential of AI technology becomes more prominent, an increasing number of enterprises are introducing AI systems to optimize human resource allocation and reduce labor costs by replacing traditional intellectual labor positions with technology. While this technological empowerment process creates convenient conditions for intelligent collaboration among employees, it also triggers potential threats to job security [2]. AI technology is catalyzing organizational transformations across various sectors and the entire value chain. Researchers explain the mechanisms through which AI technology affects employees based on dual-effect models: one is the job substitution effect, where employees may experience a sense of career crisis due to the perceived replacement by technology when AI systems are introduced, leading to negative reactions such as psychological resistance and burnout [3, 4]; the second is the capability enhancement effect, where the process of technology replacing routine tasks objectively frees up employees' cognitive resources, allowing them to focus on creative problem-solving and value creation activities. This resource reallocation effect opens up new pathways for organizational innovation performance [5]. Against this background, whether individuals can adaptively adjust their behavior patterns to effectively respond to the changing demands of job roles brought about by the evolution of employment types, thus achieving dynamic optimization and sustainable development of their career trajectories, becomes a key issue that needs to be explored in the field of employee behavior.

Therefore, this paper aims to explore the impact of organizational AI technology adoption on employees' self-directed learning behavior from the perspective of resource conservation and loss [6]. In addition, personality traits, as an important individual resource, play a crucial role. According to the resource conservation theory, individuals with high proactive personalities possess more resources and are more willing to further invest these resources, thus entering a resource gain spiral. Hence, this study intends to examine the boundary effects of proactive personality in the relationship between organizational AI adoption and employees' self-directed learning behavior.

2. Theory and hypotheses

2.1. Organizational adoption of AI technology and employees' self-directed learning behavior

The organizational adoption of Artificial Intelligence (AI) technology reflects both higher job demands and increased task difficulty on one hand, and greater autonomy and the potential for enhanced job control on the other. As part of digital transformation initiatives, the introduction of AI in the workplace brings unique job demands for employees. Therefore, organizational adoption of AI might be viewed by employees as a learning requirement, encouraging them to acquire new skills and adopt human-computer interaction models that facilitate effective problem-solving or adaptation. This duality helps cultivate employees' self-efficacy, enhances their growth motivation, and promotes the acquisition of new skills and knowledge—manifested as learning behavior. The change in job demands brought about by the organizational adoption of AI encourages employees to explore new strategies to achieve their goals, while the higher job control provided by AI technology creates space and resources for employees to alter their work. These factors collectively encourage employees' engagement in learning activities.

Hypothesis H1: Organizational adoption of AI technology positively influences employees' self-directed learning behavior.

2.2. The mediating role of job insecurity

The autonomous decision-making and execution capabilities of AI technology can break traditional job boundaries, potentially challenging employees' career stability and heightening their perceived career crisis. The adoption of AI technology by organizations will trigger the restructuring of workflows, upgrading of job skills, and transformation of labor patterns. This structural adjustment not only raises the implicit costs of career transitions but also amplifies employees' anxiety about unemployment through the job substitution effect. From the perspective of resource conservation theory, when individuals anticipate the risk of losing career resources, they are motivated to engage in compensatory behaviors, such as enhancing their skills or expanding their capabilities, to counter potential threats to career security. Relevant studies on coping strategies for job insecurity indicate that employees with high job insecurity tend to take more actions to increase their value, thus alleviating or eliminating the insecurity they experience at work [7].

Hypothesis H2: Job insecurity mediates the relationship between organizational adoption of AI technology and employees' self-directed learning behavior.

2.3. The mediating role of job crafting

Job crafting refers to employees' proactive behavior to alter their job boundaries, perceptions of work, and relational boundaries, thereby reshaping their work. Job crafting can be divided into task crafting, relational crafting, and cognitive crafting. Task crafting is particularly relevant as it involves changes in the content and scope of work, with AI technology bringing about changes in job characteristics. From a resource gain perspective, job crafting is essentially an active adaptation strategy taken by employees to optimize the allocation of work resources. The introduction of AI technology has a dual impact: it expands the channels through which individuals acquire resources via algorithms, thereby granting employees more autonomy in decision-making; additionally, by enhancing the perception of work efficiency and process control, AI not only boosts employees' confidence in completing complex tasks but also encourages them to break free from conventional problem-solving limitations.

Hypothesis H3: Job crafting mediates the relationship between organizational adoption of AI technology and employees' self-directed learning behavior.

2.4. The chain mediating role of job insecurity and job crafting

The job insecurity triggered by the organizational adoption of AI technology may activate employees' positive psychological mechanisms for proactive adaptation. Based on resource conservation theory, individuals will actively seek resources to counter potential risks of resource depletion. The process of job crafting is a form of resource-seeking behavior, and job crafting encourages adaptive changes in employees' cognitive frameworks, shifting their behavior from passive execution to active design and driving systematic career management. This ultimately forms a virtuous cycle of "environmental perception-resource investment-competency evolution," building a sustainable competitive advantage in the new paradigm of human-computer collaboration.

Hypothesis H4: Job insecurity and job crafting play a chain-mediated role in the relationship between organizational adoption of AI technology and employees' self-directed learning behavior.

2.5. The moderating role of proactive personality

The organizational adoption of AI technology has multiple impacts on employees. Individuals with a proactive personality are more likely to actively change the current situation or create new environments. They strive to achieve their goals proactively, rather than reacting passively, and are willing to take practical actions. When circumstances change, they can break through environmental limitations, explore new opportunities, and take the initiative. Therefore, the strength of employees' proactive personality influences their spontaneous behaviors. Employees with stronger proactivity will redefine their understanding of work, choose more challenging tasks, acquire more resources, and drive their self-directed learning behavior.

Hypothesis H5: Proactive personality positively moderates the relationship between job insecurity and job crafting.

3. Data collection and empirical analysis

3.1. Sample collection

This study used a questionnaire to collect data. A total of 340 participants from various industries were recruited through the Credamo platform. After data cleaning, the final valid sample size was 303 responses. Regarding the age distribution, 199 participants were between the ages of 26 and 35, accounting for nearly 65.7% of the total sample, which was the highest proportion, followed by 16.5% of participants aged 25 or younger. In terms of gender, 44.2% were male and 55.8% were female, showing a relatively even distribution. As for the educational background, the highest proportion (73.3%) of respondents held a bachelor's degree.

3.2. Measurement items

The variables in this study include organizational adoption of AI, self-directed learning behavior, etc., and they were measured using established scales from both domestic and international sources. A 5-point Likert scale was used for measurement, where 1 represented "strongly disagree" and 5 represented "strongly agree."

(1) Organizational Adoption of AI: A three-item scale adapted from Cheng et al. was used to assess the organizational adoption of AI [8]. An example item is: "My company has already adopted AI technology."

(2) Job Insecurity: A 5-item scale developed by He et al. was used to measure job insecurity [9]. One example item is: "After the company adopted AI, I am concerned that I might lose my job."

(3) Job Crafting: A 5-item scale developed by Slemp et al. was used to measure job crafting, which has been widely applied in job crafting studies [10]. An example item is: "I introduce new methods to improve my work."

(4) Self-Directed Learning Behavior: An 8-item scale developed by Bezuijen et al. was used to measure self-directed learning behavior [11]. An example item is: "I continuously learn new skills for work."

(5) Proactive Personality: A 10-item unidimensional scale, revised by Seibert et al. was used to measure proactive personality [12]. This scale is concise, has good reliability and validity, and is widely used in the measurement of proactive personality. An example item is: "I always look for better ways to handle things."

3.3. Confirmatory factor analysis

Confirmatory Factor Analysis (CFA) for this study was conducted using AMOS 26.0. The results, as shown in Table 1, indicate that the six-factor model fits the data significantly better than other models. The fit indices for the six-factor model (χ^2/df = 1.734, GFI = 0.846, RMSEA = 0.046, RFI = 0.856, CFI = 0.938, NFI = 0.866, TLI = 0.934) are clearly superior. Therefore, the measurement tools used in this study demonstrate adequate discriminant validity.

Table 1. Confirmatory factor analysis

Model	Variables	χ^2/df	GFI	RMSEA	RFI	CFI	NFI	TLI
Five-factor	X、M1、M2、Y、Z	1.734	0.946	0.046	0.916	0.938	0.866	0.934
Four-factor	X、M1+M2、Y、Z	2.736	0.813	0.068	0.821	0.877	0.805	0.868
Three-factor	X+M1+M2、Y、Z	4.332	0.531	0.097	0.64	0.716	0.661	0.698
Two-factor	X+M1+M2+Z、Y	5.095	0.517	0.108	0.577	0.65	0.601	0.629
One-factor	X+M1+M2+Y+Z	6.45	0.435	0.124	0.465	0.533	0.494	0.574

Note: X = Organizational AI Adoption; M1 = Job Insecurity; M2 = Job Crafting; Z = Proactive Personality; Y = Self-Directed Learning Behavior. "+" indicates the merging of two factors into one.

3.4. Correlation analysis

This study conducted a correlation analysis on the variable data collected through the questionnaire using SPSS 26.0 software. The results are shown in Table 2.

Table 2. Correlation analysis

Variable	M	SD	1	2	3	4	5	6	7	8
1. Gender	-	-	1							
2. Age	-	-	-0.082	1						
3. Education	-	-	-0.084	-0.025	1					
4. Organizational AI Adoption	4.297	0.653	0.073	0.078	-0.098	1				
5. Job Insecurity	3.991	0.557	0.022	0.069	-0.067	.605**	1			
6. Job Crafting	4.114	0.561	0.030	0.110	-0.107	.743**	.557**	1		
7. Self-Directed Learning Behavior	4.294	0.370	-0.016	.131*	-.125*	.699**	.580**	.709**	1	
8. Proactive Personality	4.114	0.403	-0.065	.170**	-0.050	.591**	.523**	.601**	.637**	1

3.5. Main effect and mediation effect tests

To test the relationship between organizational AI adoption, job insecurity, and job crafting, linear regression analysis was conducted. The results (see Table 3) are as follows: From Models 1 and 2, it is clear that organizational AI adoption positively affects job insecurity ($\beta = 0.510$, $p < 0.001$); from Model 4, organizational AI adoption positively affects job crafting ($\beta = 0.604$, $p < 0.001$); from Model 5, job insecurity positively affects job crafting ($\beta = 0.161$, $p < 0.001$).

Table 3. Main effect test (1)

Variable	Job Insecurity		Job Crafting		
	Model 1	Model 2	Model 3	Model 4	Model 5
Gender	0.055	-0.017	0.089	0.003	0.006
Age	-0.093	-0.040	-0.127	-0.064	-0.058
Education	-0.081	-0.003	-0.150	-0.057	-0.057
Organizational AI Adoption		0.510***		0.604***	0.522***
Job Insecurity					0.161***
F	1.888	21.828***	5.74***	50.088***	47.417***
R^2	0.043	0.373	0.12	0.577	0.593
ΔR^2	0.043	0.33	0.12	0.457	0.016

Through hierarchical regression testing (see Table 4), Model 7 shows that organizational AI adoption positively affects self-directed learning behavior ($\beta = 0.383$, $p < 0.001$), thus confirming Hypothesis H1; Model 8 shows that job insecurity positively affects self-directed learning behavior ($\beta = 0.361$, $p < 0.001$), confirming Hypothesis H2. Compared to Model 8, in Model 10, the effect of job insecurity on self-directed learning behavior decreases ($p < 0.001$). From Model 9, job crafting positively affects self-directed learning behavior ($\beta = 0.458$, $p < 0.001$). In Model 11, compared to Model 9, the β value of job crafting on self-directed learning behavior decreases to 0.268, indicating that job crafting partially mediates the effect of organizational AI adoption on self-directed learning behavior. Models 12 and 13 include both job insecurity and job crafting, and in Model 13, the β values of both job insecurity and job crafting decrease compared to Model 12, indicating that both job insecurity and job crafting mediate the relationship between organizational AI adoption and self-directed learning behavior.

Table 4. Main effect test (2)

Variable	Self-Directed Learning Behavior							
	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
Gender	0.015	-0.039	-0.005	-0.026	-0.037	-0.04	-0.027	-0.038
Age	-0.053	-0.013	-0.019	0.005	-0.007	0.004	0.009	0.007
Education	-0.100	-0.041	-0.071	-0.031	-0.041	-0.026	-0.032	-0.027
Organizational AI Adoption		0.383***			0.303***	0.221***		0.178***
Job Insecurity			0.361***		0.157***		0.176***	0.118***

Table 4. Continued

Job Crafting				0.458***		0.268***	0.361***	0.24***
F	4.142	38.402***	21.849***	38.708***	39.135***	45.071***	41.63***	43.736***
R^2	0.089	0.511	0.373	0.513	0.546	0.581	0.561	0.6
ΔR^2	0.089	0.421	0.283	0.423	0.035	0.07	0.188	0.054

As shown in Table 5, job insecurity and job crafting together mediate the positive effect between organizational AI adoption and self-directed learning behavior, with the mediation effect being significant. In the Sobel test for the organizational AI adoption—job insecurity—self-directed learning behavior path, the effect value of job insecurity is 0.063, and the 95% Confidence Interval (CI) is [0.0196, 0.1032], which does not contain 0, indicating that job insecurity significantly mediates the relationship between organizational AI adoption and self-directed learning behavior. In the Sobel test for the organizational AI adoption—job crafting—self-directed learning behavior path, the indirect effect value of job crafting is 0.1381, and the 95% CI is [0.0833, 0.1983], which does not contain 0, indicating that job crafting significantly mediates the relationship between organizational AI adoption and self-directed learning behavior. In the Sobel test for the organizational AI adoption—job insecurity—job crafting—self-directed learning behavior path, the chain mediation effect value for job insecurity and job crafting is 0.0222, and the Bootstrap 95% CI is [0.0062, 0.0457], which does not contain 0, indicating that the chain mediation effect of job insecurity and job crafting is also significant.

Table 5. Mediation effects

Path	Effect Value	BootSE	BootLLCI	BootULCI
Direct Effect	0.3964	0.0234	0.3504	0.4424
Total Indirect Effect	0.1731	0.0335	0.1073	0.239
Indirect Effect 1 (X-M1-Y)	0.063	0.0213	0.0196	0.1032
Indirect Effect 2 (X-M2-Y)	0.1381	0.0213	0.0833	0.1983
Indirect Effect 3 (X-M1-M2-Y)	0.0222	0.0101	0.0062	0.0457

3.6. Moderation effect test

This study used SPSS 24.0 software to test the moderation effect of job insecurity through hierarchical regression analysis. According to Model 4 in Table 6, the moderation effect is significant.

Table 6. Moderation effect

variable	Job Crafting			
	Model 1	Model 2	Model 3	Model 4
Gender	0.089	0.061	0.081	0.079
Age	-0.127	-0.08	-0.103	-0.102
Education	-0.15	-0.109	-0.1	-0.099
Job Insecurity		0.51***	0.308***	0.302***
Proactive Personality			0.57***	0.564***
Job Insecurity × Proactive Personality				0.019***
F	5.74	21.531***	30.682***	27.535***
R^2	0.12	0.369	0.485	0.468
ΔR^2	0.12	0.25	0.116	0.164

4. Conclusion

4.1. Research conclusions

(1) Organizational adoption of Artificial Intelligence (AI) has a significant positive impact on employees' learning behaviors. The core of this change lies in the dual nature of AI technology itself—its substitutive and enhancing functions, both of which together

constitute a direct driving force for employees' learning behavior. This may lead to two possible responses: some employees proactively seek learning opportunities due to concerns about their skills becoming obsolete, while others may become passive or even resistant due to anxiety. However, the enhancing function of AI technology offers a different set of possibilities. This type of technology simplifies complex processes and lowers operational thresholds, allowing employees to redirect their energy and space towards exploring new areas. For employees in the center of environmental change, this new work resource influences their work behavior from various angles.

(2) Job insecurity and job crafting mediate the relationship between organizational adoption of AI and employees' self-directed learning behavior. On one hand, previous studies have confirmed that the development and adoption of AI within organizations lead to employees' concerns about job instability and uncertainty about their future career development. Based on resource conservation theory, this study posits that the adoption of organizational AI technology triggers employees' self-directed learning behavior. This is because employees perceive the potential for their jobs to be replaced by AI technology, resulting in job insecurity and the perceived risk of losing their resources. In response, employees engage in proactive behaviors, such as self-directed learning, to protect and enhance their personal value in light of technological advancements.

4.2. Managerial implications

First, companies should recognize the advantages of AI technology and accelerate the process of digital transformation. Corporate managers should provide full support for the construction of digital infrastructure and foster employees' willingness to accept AI. To fully leverage the potential of AI, organizations should consider actively recruiting talent with the necessary professional knowledge and skills to provide strong talent support for the application and promotion of AI technology.

Second, companies should actively enhance technical training and take multiple measures to improve employees' AI literacy and digital adaptability. These training programs not only help employees overcome concerns and fears about AI potentially replacing their jobs but also inspire them to harness new technologies to enhance work efficiency and creativity. Moreover, organizations should assist employees in planning their career development paths within the context of AI applications. It should be clearly communicated to employees that the use of AI technology will provide them with more opportunities for career advancement.

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