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Scourge or Source of Opportunity?The Double-Edged Effect of AI Disruption Awareness on Employees' Thriving at Work

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Article

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Abstract

As artificial intelligence becomes embedded in work, employees increasingly perceive risks of job replacement and redesign. Yet how AI disruption awareness affects thriving at work remains unclear. Drawing on conservation of resources theory and the job demands–resources model, we build a dual-path chain mediation model that includes knowledge acquisition versus knowledge hiding and job security versus job insecurity, and examine the moderating roles of promotion-focused and prevention-focused job crafting. Based on a three-wave time-lagged survey of 600 full-time employees, we find that AI disruption awareness simultaneously stimulates knowledge acquisition and knowledge hiding. Knowledge acquisition enhances job security and, in turn, thriving at work, whereas knowledge hiding increases job insecurity and undermines thriving at work. Promotion-focused job crafting strengthens the resource gain path, while prevention-focused job crafting amplifies the resource loss path. These findings reveal the double-edged nature of AI disruption awareness for employees' thriving at work and enrich research on thriving and coping with AI-driven technological change.

1. Introduction

With the rapid spread of artificial intelligence (AI), organizations are embedding intelligent systems into decision-making, service and operational processes[1], reshaping employees' work boundaries, tasks and skill structures[2]. Some employees feel exhausted by intensive technological change[3], whereas others grow by learning new tools and methods[4]. Thriving at work, which combines vitality and learning[5], is vital for employees' health and performance and for organizational resilience and innovation[6]. Prior studies show that thriving mainly depends on job characteristics, leadership and individual traits[7], but we still know little about how new digital technologies—especially AI—and the subjective disruption they create influence thriving at work.

AI disruption awareness, defined as employees' perception of AI-related risks [8]such as job replacement, skill devaluation and work redesign, has been linked to job satisfaction, turnover intention and innovative behavior[9], but its impact on this higher-order state of thriving remains unclear. From a resource perspective, AI disruption awareness is a double-edged situational signal[10]. On the one hand, technological updates bring knowledge pressure and job uncertainty, which may trigger job insecurity, emotional exhaustion and withdrawal[11, 12]. On the other hand, intelligent technologies offer new tools and learning opportunities that help employees enhance capabilities and expand roles[13, 14]. Some employees respond by attending training and increasing knowledge acquisition[15], while others reduce knowledge sharing or even engage in knowledge hiding for self-protection[16]. Thus, AI disruption awareness may foster resource gain through knowledge acquisition and job security[17], or drive resource loss through knowledge hiding and job insecurity, leading to very different levels of thriving at work[18].

Employees are not passive recipients of technological shock; they can actively adjust person–job fit through job crafting[19]. Promotion-focused job crafting emphasizes expanding tasks and seeking resources and challenges, making employees more likely to view AI as an opportunity[20], engage with new systems and redesign workflows, thereby strengthening knowledge acquisition and job security[21]. Prevention-focused job crafting emphasizes reducing hindering demands and avoiding risks, leading employees to narrow their task scope, distance themselves from AI-related work and retain key information[19], which reinforces knowledge hiding and job insecurity[22]. Job crafting orientations may therefore serve as important boundary conditions linking AI disruption awareness to thriving at work.

Based on the above discussion, this study focuses on the following three research questions:

Q1: Does AI disruption awareness promote or undermine employees' thriving at work, or does it exert a double-edged effect?

Q2: Through which mechanisms does AI disruption awareness influence thriving at work? Specifically, do knowledge acquisition and job security form a resource gain path, while knowledge hiding and job insecurity form a resource loss path?

Q3: Under what conditions are these two paths strengthened or weakened? In particular, how do promotion-focused and prevention-focused job crafting shape the effects of AI disruption awareness on employees' knowledge behaviors, job security perceptions and thriving at work?

To answer these questions, this study develops a dual-path chain mediation model based on conservation of resources theory and the job demands–resources model. Specifically, we examine whether AI disruption awareness promotes thriving at work through knowledge acquisition and job security, and whether it undermines thriving at work through knowledge hiding and job insecurity. We further investigate whether promotion-focused job crafting strengthens the resource gain path and whether prevention-focused job crafting amplifies the resource loss path. By doing so, this study aims to clarify the double-edged effect of AI disruption awareness and explain why some employees thrive under AI-driven technological change, whereas others experience reduced vitality and learning.

The remainder of this article is organized as follows. Section 2 develops the theoretical framework and research hypotheses by explaining the resource gain path, the resource loss path and the moderating role of job crafting. Section 3 presents the research design, including the measures, data collection procedure and sample characteristics. Section 4 reports the data analysis and empirical results, including reliability and validity tests, descriptive statistics, correlation analysis, mediation tests and moderated chain mediation tests. Section 5 discusses the conclusions, theoretical contributions, managerial implications, limitations and directions for future research.

2. Theoretical Analysis and Research Hypotheses

2.1. Resource Gain and Motivational Process: Positive Path of AI Disruption Awareness

Conservation of resources (COR) theory suggests that individuals strive to obtain, retain and protect valuable resources, and perceived threats to such resources may trigger corresponding coping responses[23]. The job demands–resources (JD–R) model further argues that work experiences are shaped by job demands, which consume effort, and job resources, which support goal achievement and personal growth[24]. In the context of AI-driven technological change, AI disruption awareness reflects employees' perception that AI may replace jobs, devalue skills or reshape work roles[8]. Such awareness may increase perceived pressure, but it may also stimulate employees to acquire new resources to cope with future work demands.

Prior studies on technological change and employee adaptation have shown that external disruption can motivate individuals to update their knowledge and improve employability when the disruption is viewed as manageable or developmental[18]. From the COR perspective, when employees perceive possible resource loss, such as declining skill value or occupational stability, they may compensate by acquiring new knowledge and competencies[25]. In AI-related work settings, changing task requirements and the spread of intelligent tools make prior knowledge less sufficient, while digital learning channels also lower the cost of learning. Thus, employees with stronger AI disruption awareness may become more motivated to seek and absorb new work-related knowledge[26].

H1a. AI disruption awareness positively predicts employees' knowledge acquisition.

Knowledge acquisition may further strengthen employees' job security. In the JD–R model, knowledge and skills are important job resources because they help employees handle changing demands and achieve work goals[24]. Employees who participate in training, use learning platforms and interact with colleagues can improve their human capital and task competence[27]. In an AI-driven environment, such competence makes employees feel more adaptable, less replaceable and more employable[28]. Therefore, knowledge acquisition helps employees build a psychological buffer against technological uncertainty and enhances their confidence in job stability.

H2a. Knowledge acquisition positively affects employees' job security.

Job security provides a foundation for thriving at work, which refers to a positive psychological state combining vitality and learning[5]. Existing research suggests that thriving requires sufficient psychological and work resources[6]. Job security reflects employees' belief that their current job is relatively stable and unlikely to be lost or seriously downgraded[29]. When employees feel secure, they can devote less energy to worrying about job loss and more energy to learning, experimentation and work engagement. These conditions directly support vitality and learning at work[30].

H3a. Employees' job security promotes their thriving at work.

Taken together, AI disruption awareness may promote thriving at work through a sequential resource gain process. Employees who perceive AI disruption may actively acquire knowledge to improve their competence. This competence then enhances job security, allowing employees to invest more energy in work and self-development. This chain reflects the resource accumulation logic of COR theory[17], in which the gain of one resource facilitates further resource gains and positive psychological outcomes.

H4a. AI disruption awareness enhances employees' thriving at work through a chain mediation of knowledge acquisition and job security.

2.2. Resource Loss and Depletion Process: Negative Path of AI Disruption Awareness

AI disruption awareness may also activate a defensive resource protection process. COR theory emphasizes that individuals are often more sensitive to resource loss than to resource gain, especially when important resources are threatened[23]. In the workplace, knowledge is a valuable personal resource because it supports employees' status, performance and perceived irreplaceability. When employees strongly perceive AI-related replacement or marginalization risks, they may regard knowledge as a scarce resource that should be protected rather than shared[11].

Knowledge hiding refers to an intentional attempt to conceal or withhold knowledge requested by others, such as refusing to share information, providing evasive responses or pretending not to know[31]. In AI-driven workplaces, employees with high AI disruption awareness may hide knowledge to maintain uniqueness, reduce others' access to their expertise and preserve competitive advantage[13]. Although this strategy may appear protective in the short term, it reflects a defensive response focused on guarding existing resources rather than creating new ones.

H1b. AI disruption awareness positively predicts employees' knowledge hiding.

Knowledge hiding may further intensify job insecurity. Prior studies show that knowledge hiding weakens interpersonal trust, reduces cooperation and limits mutual support in teams[16]. Employees who hide knowledge may also lose opportunities for reciprocal learning and resource exchange. In a rapidly changing AI environment, this can slow their own knowledge renewal and increase concerns about skill obsolescence[31]. From a COR perspective, knowledge hiding may temporarily prevent knowledge outflow, but it also blocks new resource acquisition and weakens social support, thereby increasing job insecurity[14].

H2b. Knowledge hiding positively affects employees' job insecurity.

Job insecurity reflects employees' perception that their job or valued job features are threatened. Prior research indicates that persistent job insecurity consumes psychological resources and shifts employees' attention from learning and innovation to job preservation[32]. In the AI context, uncertainty about skill usefulness and role continuity may reduce work enthusiasm and learning motivation[15]. Since thriving at work requires both vitality and learning, sustained job insecurity is likely to undermine employees' thriving state[33].

H3b. Job insecurity negatively affects employees' thriving at work.

Taken together, AI disruption awareness may reduce thriving at work through a sequential resource loss process. Employees who perceive AI as a strong threat may engage in knowledge hiding to protect existing advantages[16]. However, this defensive behavior weakens trust, limits knowledge exchange and reduces opportunities for support and learning, which increases job insecurity[28]. As job insecurity accumulates, employees' psychological resources are further depleted, making it difficult to remain energetic and learning-oriented at work.

H4b. AI disruption awareness undermines employees' thriving at work through a chain mediation of knowledge hiding and job insecurity.

2.3. Moderating Role of Job Crafting

Employees differ in how they proactively adjust their jobs when facing AI disruption. Job crafting refers to employees' self-initiated changes in task boundaries, work methods, social interactions or work cognition to improve person–job fit[2]. Prior studies distinguish between promotion-focused and prevention-focused job crafting. Promotion-focused job crafting emphasizes increasing structural resources, social resources and challenging demands, whereas prevention-focused job crafting emphasizes reducing or avoiding hindering demands[19, 20]. These two orientations may determine whether AI disruption awareness is more likely to be transformed into knowledge acquisition or knowledge hiding.

Promotion-focused job crafting may strengthen the relationship between AI disruption awareness and knowledge acquisition. Employees high in promotion-focused job crafting tend to seek resources, expand task boundaries and take on challenges[19]. When perceiving AI disruption, they are more likely to view AI as an opportunity to improve competence, actively learn AI tools, participate in training, consult colleagues and redesign work processes[20]. Therefore, the positive effect of AI disruption awareness on knowledge acquisition should be stronger when promotion-focused job crafting is high.

Prevention-focused job crafting may strengthen the relationship between AI disruption awareness and knowledge hiding. Employees high in prevention-focused job crafting tend to reduce pressure by avoiding hindering demands and limiting exposure to risks[19]. When perceiving AI disruption, they may be more likely to withdraw from AI-related tasks, avoid comparison with others and protect existing knowledge advantages through concealment.

H5a. Promotion-focused job crafting positively moderates the relationship between AI disruption awareness and knowledge acquisition, such that the positive effect is stronger when promotion-focused job crafting is high.

H5b. Prevention-focused job crafting positively moderates the relationship between AI disruption awareness and knowledge hiding, such that the positive effect is stronger when prevention-focused job crafting is high.

2.4. Moderated Chain Mediation

The above hypotheses suggest that AI disruption awareness influences thriving at work through two resource trajectories. A resource gain path from knowledge acquisition to job security and then to thriving, and a resource loss path from knowledge hiding to job insecurity and then to reduced thriving. However, the strength of these two paths may depend on employees' job crafting orientations.

On the positive path, employees high in promotion-focused job crafting are better able to convert AI-related pressure into learning actions and apply newly acquired knowledge to task redesign[34], capability improvement and performance enhancement[29]. As a result, knowledge acquisition is more likely to generate job security and further support vitality and learning at work[35]. Therefore, when promotion-focused job crafting is high, the positive chain effect of AI disruption awareness on thriving through knowledge acquisition and job security should be stronger.

H6a. Promotion-focused job crafting positively moderates the chain mediating effect of knowledge acquisition and job security between AI disruption awareness and thriving at work, such that this positive chain effect is stronger when promotion-focused job crafting is high.

On the negative path, employees high in prevention-focused job crafting are more likely to respond to AI disruption by avoiding risks, narrowing task involvement and protecting existing resources[37]. Such employees may engage more frequently in knowledge hiding and avoid AI-related learning opportunities[38], which accelerates the accumulation of job insecurity and weakens their ability to maintain vitality and learning[40]. Therefore, when prevention-focused job crafting is high, the negative chain effect of AI disruption awareness on thriving through knowledge hiding and job insecurity should be stronger.

H6b. Prevention-focused job crafting positively moderates the chain mediating effect of knowledge hiding and job insecurity between AI disruption awareness and thriving at work, such that this negative chain effect is stronger when prevention-focused job crafting is high.

In sum, this study proposes a double-edged mechanism of AI disruption awareness. Specifically, AI disruption awareness may enhance thriving at work through knowledge acquisition and job security, while it may also undermine thriving at work through knowledge hiding and job insecurity. Promotion-focused and prevention-focused job crafting serve as boundary conditions that strengthen the positive and negative paths, respectively. The proposed theoretical model is shown in Fig. 1.

3. Research Design

3.1. Measures

This study examined AI disruption awareness (independent variable), thriving at work (dependent variable), four mediators (knowledge acquisition, knowledge hiding, job security, job insecurity), two moderators (promotion-focused job crafting, prevention-focused job crafting) and demographic controls. All constructs were measured with established Chinese or international scales following a translation–back-translation–pilot procedure, using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Cronbach's α values ranged from 0.734 to 0.797.

AI disruption awareness (AIS) was measured with a five-item scale by Brougham and Haar [3](e.g., "I think my job could possibly be replaced by AI").

Thriving at work (THR) was measured with the 10-item scale by Porath et al.[36], covering vitality and learning (e.g., "At work, I often proactively learn new things").

Knowledge acquisition (KA) was measured with a four-item scale by Huang [34] (e.g., "I make full use of various training and learning opportunities provided by the company").

Knowledge hiding (KH) was measured with a four-item scale adapted from Connelly et al. [37] and Rhee et al. [38] (e.g., "I pretend not to know this information").

Job security (JS) was measured with a four-item scale adapted from Oldham et al.[39](e.g., "My job position has a high level of stability and security").

Job insecurity (JI) was measured with a four-item scale by Hellgren [40] (e.g., "I am worried that I might lose my current job due to changes").

Promotion-focused and prevention-focused job crafting were measured with the job crafting scale by Tims and Bakker [41], combined with Lichtenthaler and Fischbach [42]. Promotion-focused job crafting (PJC) (15 items) captures increasing structural and social resources and challenge demands (e.g., "I try to improve my abilities through effort"); prevention-focused job crafting (NJC) (6 items) reflects reducing hindering job demands (e.g., "I try to lessen the stress caused by work").

Gender, age, education, tenure, job level and daily AI use frequency were included as control variables.

3.2. Data Collection

Data were collected through a three-wave online survey over three weeks on Wenjuanxing to time-separate the independent variable, mediators and outcome and reduce common method bias. Wave 1 measured AI disruption awareness and job crafting; Wave 2 measured knowledge acquisition, knowledge hiding, job security and job insecurity; Wave 3 measured thriving at work.

Wave 1 yielded 628 responses; after quality checks, 614 valid cases remained. Wave 2 produced 605 valid responses from these participants; Wave 3 produced 600 valid matched three-wave samples.

Most respondents were aged 25–35 years; about 49% were male; 52.67% held a bachelor's degree or above; 56% had more than five years of work experience; and 53.5% reported using AI tools for more than two hours per day, indicating a sample with relatively high AI exposure.

4. Data Analysis and Results

4.1. Reliability Analysis

Using SPSS 27.0, we examined the reliability of all study variables. As shown in Table 1, Cronbach's α coefficients for all scales were above 0.70, indicating good internal consistency and supporting subsequent statistical analyses.

Table 1
Reliability Coefficients of the Scales.

Variable	Cronbach's α	Number of items
AIS	0.775	5
KA	0.765	4
KH	0.785	4
JS	0.784	4
JI	0.797	4
THR	0.734	10
PJC	0.733	15
NJC	0.789	6

Subsequently, KMO and Bartlett's tests were conducted for each variable (Table 2). All eight scales had KMO values above 0.70 and significant Bartlett's tests, indicating adequate sampling and suitability for factor analysis. On this basis, confirmatory factor analysis was performed in AMOS 27.0, comparing the proposed eight-factor model with several alternative models (Table 3). The eight-factor model showed good fit (χ^2 = 1342.398, df = 1246, SRMR = 0.03,

CFI = 0.984, TLI = 0.983, RMSEA = 0.011), meeting or exceeding common criteria and clearly outperforming the merged models, which indicates good construct validity and discriminant validity.

Table 2
KMO and Bartlett's Test for Each Variable.

Variable	Number of items	KMO value	χ2	df	Sig.
AIS	5	0.824	691.583	10	< 0.001
KA	4	0.782	557.967	6	< 0.001
KH	4	0.79	637.887	6	< 0.001
JS	4	0.788	641.09	6	< 0.001
JI	4	0.795	689.04	6	< 0.001
THR	10	0.851	733.493	45	< 0.001
PJC	15	0.849	838.337	105	< 0.001
NJC	6	0.860	821.294	15	< 0.001

Table 3
Confirmatory Factor Analysis.

Model	χ2	df	χ2/df	SRMR	CFI	TLI	RMSEA
Eight-factor model	1342.398	1246	1.077	0.030	0.984	0.983	0.011
Seven-factor model	2037.550	1253	1.626	0.045	0.872	0.846	0.032
Six-factor model	2257.410	1259	1.793	0.045	0.837	0.828	0.036
Five-factor model	3052.783	1264	2.415	0.061	0.708	0.694	0.049
Four-factor model	3540.204	1268	2.792	0.066	0.629	0.612	0.055
Three-factor model	4365.090	1271	3.434	0.075	0.495	0.437	0.064
Two-factor model	4846.177	1273	3.807	0.076	0.416	0.392	0.068
One-factor model	5551.727	1274	4.358	0.083	0.301	0.273	0.075

4.2. Common Method Bias and Multicollinearity Tests

To test common method bias, Harman's single-factor exploratory factor analysis was conducted. Multiple factors were extracted, and the first factor accounted for only 10.172% of the total variance (< 40%), indicating that no single factor dominated the variance. Together with the confirmatory factor analysis results showing that the single-factor model fit was substantially worse than the eight-factor model, this suggests that common method bias is unlikely to be a serious problem.

Before multivariate regression, multicollinearity was also examined. The variance inflation factors (VIFs) for the main independent and mediating variables ranged from 1.003 to 9.526, all below the common threshold of 10, indicating no serious multicollinearity.

4.3. Descriptive Statistics and Correlation Analysis

SPSS 27.0 was used to compute descriptive statistics and correlations among the variables (Table 4). AI disruption awareness was positively correlated with knowledge acquisition (r = 0.418), knowledge hiding (r = 0.366), job security (r = 0.264) and job insecurity (r = 0.211) (all p < 0.01), but was not significantly correlated with thriving at work (r = − 0.009), suggesting mainly indirect effects. Knowledge acquisition was positively correlated with job security (r = 0.479), and knowledge hiding with job insecurity (r = 0.479). Job security was positively correlated with thriving at work (r = 0.222), whereas job insecurity was negatively correlated with thriving at work (r = − 0.275) (all p < 0.01). These patterns are broadly consistent with the theoretical model and provide preliminary support for the dual-path mechanism whereby AI disruption awareness affects thriving at work through knowledge behaviors and job (in)security.

Table 4
Descriptive statistics and correlations among main variables.

1.Gender	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
	1.51	**0.50**													
2.Age	2.50	1.09	-0.005												
3.Edu	2.63	0.83	-0.019	-0.001											
4.Tenure	2.51	1.10	-0.009	.940**	0.005										
5.Job level	2.22	0.95	0.018	.787**	.091*	.765**									
6.AI use frequency	2.57	1.07	0.005	-0.034	0.033	-0.026	0.015								
7.AIS	2.99	0.67	-0.044	-0.011	-0.021	-0.024	0.021	.122**							
8.KA	2.97	0.70	-0.009	-0.008	0.009	-0.021	0.003	0.045	.418**						
9.KH	3.00	0.70	-0.01	0.021	0.027	0.014	0.033	-0.019	.366**	.156**					
10.JS	3.06	0.70	-0.072	-0.045	-0.032	-0.054	-0.029	-0.003	.264**	.479**	.116**				
11.JI	2.98	0.76	0.026	0.034	-0.012	0.041	0.051	− .091*	.211**	.085*	.479**	0.075			
12.THR	2.98	0.50	0.045	-0.032	0.038	-0.04	-0.053	0.015	-0.009	.134**	− .111**	.222**	− .275**		
13.PJC	2.98	0.42	0.017	0.026	0.024	0.017	0.008	-0.029	0.025	0.058	0.048	0.038	0.014	0.018	
14.NJC	3.05	0.65	0.026	-0.002	-0.034	-0.005	-0.012	-0.054	0.073	0.032	0.07	0.003	.121**	-0.04	0.00

Note: N = 600. AIS = AI disruption awareness; KA = knowledge acquisition; KH = knowledge hiding; JS = job security; JI = job insecurity; THR = thriving at work PJC = promotion-focused job crafting; NJC = prevention-focused job crafting. * p < 0.05, ** p < 0.01.

4.4. Hypothesis Testing

4.4.1. Resource Gain and Motivational Process: Positive Path of AI Disruption Awareness

Controlling for gender, age, education, tenure, job level and AI use frequency, the regression results (Table 5) show that AI disruption awareness has a significant positive effect on knowledge acquisition (β = 0.419, R^2 = 0.176, p < 0.01), supporting H1a. Knowledge acquisition significantly increases job security (β = 0.479, R^2 = 0.238, p < 0.01), supporting H2a. Job security significantly promotes thriving at work (β = 0.228, R^2 = 0.059, p < 0.01), supporting H3a and confirming the positive path at the regression level.

Table 5
Regression analysis for the positive path.

Variable		KA		JS		THR	
		β	SE	β	SE	β	SE
Controls	Gender	0.01	0.052	-0.069	0.05	0.064	0.04
	Age	0.067	0.073	-0.017	0.07	0.093	0.056
	Education	0.019	0.032	-0.039	0.03	0.054	0.024
	Tenure	-0.067	0.07	-0.047	0.067	-0.045	0.053
	Job level	-0.01	0.045	0.024	0.043	-0.091	0.034
	AI use frequency	-0.006	0.025	-0.025	0.023	0.017	0.019
Predictors	AIS	0.419***	0.04				
	KA			0.479***	0.036		
	JS					0.228***	0.029
	R2	0.176		0.238		0.059	
	Adjusted R^2	0.166		0.229		0.048	
	F	18.023***		26.422***		5.347***	

Note: * p < 0.1, ** p < 0.05, *** p < 0.01.

Bootstrapped mediation results (Table 6) show that the direct effect of AI disruption awareness on thriving at work is − 0.0923 (95% CI [− 0.1336, − 0.0039]), which is significantly negative. The chain mediating effect through knowledge acquisition and job security is 0.0413 (95% CI [0.0168, 0.048]), which is significantly positive, supporting H4a. Overall, the positive indirect effect is smaller than the negative direct effect, making the total effect of AI disruption awareness on thriving at work slightly negative and further confirming its double-edged nature.

Table 6
Bootstrap analysis of the chain mediating effect of knowledge acquisition and job security.

Effect	**Effect value**	**SE**	**95% CI**	
			Lower	**Upper**
Direct effect	-0.0923	0.033	-0.1336	-0.0039
Chain mediating effect	0.0413	0.0106	0.0168	0.048
Note: Bootstrap Samples = 5000				

4.4.2. Resource Loss and Depletion Process: Negative Path of AI Disruption Awareness

Controlling for gender, age, education, tenure, job level and AI use frequency, the regression results (Table 7) show that AI disruption awareness significantly and positively predicts knowledge hiding (β = 0.375, p < 0.01). Knowledge hiding significantly increases job insecurity (β = 0.478, p < 0.01), and job insecurity significantly reduces thriving at work (β = −0.274, p < 0.01). These results support H1b–H3b.

Table 7
Regression analysis for the negative path.

Variable		KH		JI		THR	
		β	SE	β	SE	β	SE
Controls	Gender	0.008	0.054	0.03	0.054	0.054	0.039
	Age	0.015	0.076	-0.11	0.077	0.074	0.055
	Education	0.036	0.033	-0.027	0.033	0.042	0.024
	Tenure	-0.003	0.072	0.098	0.073	-0.05	0.052
	Job level	0.013	0.047	0.05	0.047	-0.063	0.034
	AI use frequency	-0.065	0.025	-0.083*	0.025	-0.01	0.018
Predictors	AIS	0.375***	0.041				
	KH			0.478***	0.039		
	JI					-0.274***	0.026
	R2	0.14		0.241		0.082	
	Adjusted R^2	0.13		0.232		0.071	
	F	13.776***		26.808***		7.577***	
Note: * p < 0.1, ** p < 0.05, *** p < 0.01.							

Bootstrapped mediation results (Table 8) further show that the direct effect of AI disruption awareness on thriving at work is not significant (0.0562, 95% CI [− 0.021, 0.1407]), whereas the chain mediating effect via knowledge hiding and job insecurity is significantly negative (− 0.0103, 95% CI [− 0.0717, − 0.0313]), supporting H4b and indicating that, along this path, AI disruption awareness mainly undermines thriving at work through indirect effects.

Table 8
Bootstrap analysis of the chain mediating effect of knowledge hiding and job insecurity.

Effect	**Effect value**	**SE**	**95% CI**	
			Lower	**Upper**
Direct effect	**0.0562**	0.032	-0.021	0.1047
Chain mediating effect	-0.0499	0.0103	-0.0717	-0.0313
Note: Bootstrap Samples = 5000				

4.4.3. Moderating Effects of Job Crafting

Hierarchical regression analyses in SPSS 27.0 were used to test the moderating effects of job crafting (Table 9). With knowledge acquisition as the dependent variable, adding AI disruption awareness increased R^2 to 0.176 and its main effect was significantly positive ($\beta = 0.419$, $p < 0.01$). After including the interaction between AI disruption awareness and promotion-focused job crafting, R^2 rose to 0.188 ($\Delta R^2 = 0.010$), and the interaction term was significantly positive ($\beta = 0.2657$, $p < 0.01$), supporting H5a.

With knowledge hiding as the dependent variable, AI disruption awareness positively predicted knowledge hiding ($\beta = 0.375$, $R^2 = 0.140$, $p < 0.01$). After adding the interaction between AI disruption awareness and prevention-focused job crafting, R^2 increased to 0.179 ($\Delta R^2 = 0.038$), and the interaction term was significantly positive ($\beta = 0.3176$, $p < 0.01$), supporting H5b. These results (Fig. 2) indicate that promotion-focused and prevention-focused job crafting respectively strengthen the positive (a) and negative paths (b).

Table 9
Results of moderating effect tests (hierarchical regression). Note: N = 600

		KA				KH			
		M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**
Control variables	Gender	-0.01	0.01	0.009	0.0105	-0.01	0.008	0.007	0.0037
	Age	0.092	0.067	0.062	0.0424	0.038	0.015	0.014	0.0044
	Education	0.005	0.019	0.018	0.0185	0.024	0.036	0.037	0.028
	Tenure	-0.126	-0.067	-0.064	-0.0434	-0.056	-0.003	-0.003	0.0051
	Job level	0.025	-0.01	-0.008	-0.0061	0.044	0.013	0.014	0.0044
	AI use frequency	0.044	-0.006	-0.005	-0.0058	-0.02	-0.065*	-0.063	-0.0518**
Predictor	AIS		0.419***	0.417***	0.4354***		0.375***	0.372***	0.3935***
Moderator	PJC			0.046	0.0794			0.041	
	NJC								0.0549
Interaction terms	AIS*PJC				0.2657***				
	AIS*NJC								0.3176***
Fit index	R2	0.004	0.176	0.178	0.1878	0.003	0.14	0.142	0.1794
	ΔR2	0.004	0.172	0.002	0.01	0.003	0.138	0.002	0.0377
	F	0.407	18.023***	15.971***	15.1537***	0.254	13.776***	12.199***	14.336***

Note：N=600；

4.4.4. Moderated Chain Mediation

As shown in Table 10, when promotion-focused job crafting is low (M − SD) and high (M + SD), the indirect effects of AI disruption awareness on thriving at work via knowledge acquisition and job security are 0.0228 and 0.0383, respectively; both 95% confidence intervals exclude zero, and their difference interval [0.0091, 0.0229] also excludes zero, supporting H6a. When prevention-focused job crafting is low and high, the indirect effects via knowledge hiding and job insecurity are − 0.0176 and − 0.0563, respectively; again, both 95% confidence intervals and their difference interval [− 0.0483, − 0.0301] exclude zero, supporting H6b. Overall, promotion-focused job crafting amplifies the resource gain chain, whereas prevention-focused job crafting strengthens the resource loss chain, further highlighting the double-edged nature of AI disruption awareness.

Table 10
Results of moderated chain mediation effects.

Group	**Indirect effect**	**SE**	**95% CI**	
			Lower	**Upper**
Low promotion-focused job crafting (M-SD)	0.0228	0.0064	0.0114	0.0367
High promotion-focused job crafting (M + SD)	0.0383	0.0077	0.0205	0.0596
Difference	0.0155	0.0013	0.0091	0.0229
Low prevention-focused job crafting (M-SD)	-0.0176	0.0062	-0.0307	-0.0065

Continued Table 10. Results of moderated chain mediation effects.

High prevention-focused job crafting (M + SD)	**-0.0563**	**0.011**	**-0.079**	**-0.0366**
Difference	-0.0387	0.0048	-0.0483	-0.0301
Note: Bootstrap Samples = 5000				

5. Conclusions and Discussion

5.1. Conclusions

Drawing on conservation of resources theory and the job demands–resources model, this study examined the double-edged effect of AI disruption awareness on employees' thriving at work. Based on a three-wave time-lagged survey of 600 full-time employees, the results show that AI disruption awareness is not a purely negative threat or a naturally positive opportunity. Instead, it affects thriving at work through two opposite resource paths.

First, AI disruption awareness promotes knowledge acquisition, which further enhances job security and ultimately improves thriving at work. This finding supports the resource gain path, suggesting that when employees respond to AI disruption by learning new knowledge and strengthening their competence, they are more likely to develop confidence in job stability and experience higher levels of vitality and learning at work.

Second, AI disruption awareness also increases knowledge hiding, which further strengthens job insecurity and finally reduces thriving at work. This finding supports the resource loss path, suggesting that when employees respond to AI disruption through defensive knowledge protection, they may weaken knowledge exchange and social support, intensify perceived job threat and become less able to maintain energy and learning at work.

Third, job crafting plays an important boundary role in these two paths. Promotion-focused job crafting strengthens the positive chain effect of AI disruption awareness on thriving at work through knowledge acquisition and job security, whereas prevention-focused job crafting strengthens the negative chain effect through knowledge hiding and job insecurity. These findings indicate that the effect of AI disruption awareness depends not only on the intensity of perceived technological shock, but also on how employees actively reshape their work in response to such shock.

5.2. Discussion

This study both confirms and extends existing research on AI disruption awareness, employee knowledge behavior, job security perceptions and thriving at work. Previous studies have shown that AI and related intelligent technologies may create job replacement anxiety, increase job insecurity and trigger negative employee reactions such as emotional exhaustion, withdrawal or maladaptive workplace behavior. Consistent with this line of research, our findings show that AI disruption awareness can activate a resource loss process. Specifically, employees who perceive stronger AI-related threats are more likely to engage in knowledge hiding, which increases job insecurity and ultimately undermines thriving at work. This result supports the view that AI-driven technological change may operate as a threat-related work demand when employees focus mainly on possible resource loss.

At the same time, the findings are also consistent with research emphasizing the positive side of technological change. Prior studies have suggested that employees may treat AI as a learning opportunity, acquire new knowledge and improve their adaptability when they perceive technological change as manageable or developmental. In line with this view, this study finds that AI disruption awareness can stimulate knowledge acquisition, enhance job security and promote thriving at work. This result indicates that AI-related pressure does not necessarily lead to negative outcomes. When employees convert technological pressure into learning motivation, AI disruption awareness may become a starting point for resource accumulation.

However, this study differs from much previous research in several important ways. Many existing studies examine either the negative consequences or the positive consequences of AI disruption awareness separately. By contrast, this study places both effects in the same model and shows that AI disruption awareness simultaneously promotes knowledge acquisition and knowledge hiding. This means that employees' reactions to AI disruption are not simply positive or negative, but ambivalent and resource-dependent. The same technological shock may lead some employees to learn and grow, while leading others to protect existing knowledge and withdraw from resource exchange.

Previous studies on AI disruption have often focused on outcomes such as job satisfaction, turnover intention, innovation behavior, service performance or emotional exhaustion. This study shifts the outcome focus to thriving at work, a higher-order positive psychological state combining vitality and learning. In doing so, it extends the literature on the antecedents of thriving at work from traditional factors such as leadership, work characteristics and individual traits to the context of AI-driven technological change. The findings suggest that thriving at work in the AI era depends not only on whether employees face technological pressure, but also on whether such pressure is transformed into resource gain or resource loss.

This study contributes to the literature by clarifying the sequential mechanism from knowledge behavior to job security perception. Existing studies have separately examined knowledge acquisition, knowledge hiding, job security and job insecurity, but fewer studies have linked these variables into two complete resource chains. The present findings show that knowledge acquisition and job security form a resource gain chain, while knowledge hiding and job insecurity form a resource loss chain. This provides a more detailed explanation of how AI disruption awareness is translated into different psychological outcomes.

Prior job crafting research has generally suggested that proactive work adjustment can improve person–job fit and positive work outcomes. Our results further show that different types of job crafting may have different consequences under AI disruption. Promotion-focused job crafting helps employees transform AI-related pressure into learning and security, whereas prevention-focused job crafting may amplify defensive responses and insecurity. This

distinction enriches job crafting research by showing that job crafting is not uniformly beneficial; its effect depends on whether employees craft their jobs toward growth and resource expansion or toward avoidance and risk reduction.

The findings also have practical implications. Organizations should not assume that AI adoption will automatically improve employee growth, nor should they treat employee anxiety as a purely individual problem. Instead, AI implementation should be accompanied by training systems, transparent communication and career development support. Managers can reduce the negative effect of AI disruption awareness by encouraging knowledge acquisition, building a knowledge-sharing climate and improving employees' perceived job security. At the same time, organizations should pay attention to excessive prevention-focused job crafting, because avoiding AI-related tasks or protecting knowledge defensively may deepen insecurity and weaken thriving. Encouraging promotion-focused job crafting, such as learning AI tools, redesigning work processes and seeking new challenges, may help employees transform AI disruption into a developmental opportunity.

Overall, the main contribution of this study lies in revealing the double-edged mechanism of AI disruption awareness. It integrates the positive and negative paths into one framework, explains the transition from AI-related perception to knowledge behavior and job security perception, and identifies job crafting orientations as key boundary conditions. These findings provide a more balanced understanding of how employees can either thrive or decline under AI-driven technological change.

Although this study provides useful findings, several limitations remain. First, the data were collected through self-report online surveys from a domestic sample. Future research could use multi-source data, such as supervisor ratings, coworker ratings and objective organizational indicators, and further test the model across different industries, regions and cultural contexts. Second, although this study adopted a three-wave time-lagged design, it cannot fully capture the long-term dynamics of resource gain and resource loss. Future studies could use longitudinal designs, growth models or experience sampling methods to examine how employees' reactions to AI disruption change over time. Third, this study mainly focused on knowledge behavior and job security perception. Future research may include other mechanisms, such as emotional exhaustion, work meaning, career identity and perceived employability. Finally, job crafting was divided into promotion-focused and prevention-focused orientations in this study. Future research could further distinguish task crafting, relational crafting and cognitive crafting, and examine how different types and intensities of AI disruption shape employees' crafting behaviors and thriving at work.

Declarations

Data Availability Statement

The datasets generated and/or analysed during the current study are not publicly available due to the sensitive nature of the information collected (including employees' work attitudes, psychological states, and perceptions of AI-related risks) and the confidentiality commitments made to participants during the informed consent process. However, de-identified data are available from the corresponding author upon reasonable request, subject to approval by the relevant institutional ethics review board and appropriate data usage agreements. The questionnaire used in this study, the variable coding scheme, and a detailed description of all analysis procedures are provided as Supplementary Materials and are also available via the **Science Data Bank (ScienceDB)** repository for peer review purposes at the following **anonymous private link**: https://www.scidb.cn/anonymous/WVY3QkZ6. No custom code or script was generated for this study; all analyses were conducted using standard statistical software (SPSS version 27.0 and AMOS version 27.0) with point-and-click procedures, which are fully documented in the supplementary analysis description.

Ethics Declarations

Ethics approval: This study was reviewed by the Animal Ethics Committee of Dalian Polytechnic University. As this committee is exclusively mandated to review research involving animal subjects and does not have the jurisdiction to review human participant research, formal ethics approval for this study was waived.

The exemption is granted in accordance with Article 32 of the Measures for the Ethical Review of Life Sciences and Medical Research Involving Humans (Guo Wei Ke Jiao Fa [2023] No. 4)[1], which stipulates that ethical review may be waived for research using anonymized information data that does not cause harm to human subjects, does not involve sensitive personal information, and does not involve commercial interests. This study involved an anonymous, non-interventional online questionnaire survey that did not collect any personally identifiable information (e.g., names, ID numbers, IP addresses, or contact details) and posed no more than minimal risk to participants. The research therefore falls within the scope of exemption under the aforementioned regulation.

All research was performed in accordance with the Declaration of Helsinki and the relevant institutional ethical guidelines and regulations. Informed consent was obtained from all participants prior to their participation in the study.

[1] Measures for the Ethical Review of Life Sciences and Medical Research Involving Humans (Guo Wei Ke Jiao Fa [2023] No. 4), Article 32. Available at: https://www.nhc.gov.cn/qjjys/c100016/202302/6b6e447b3edc4338856c9a652a85f44b.shtml

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Figures

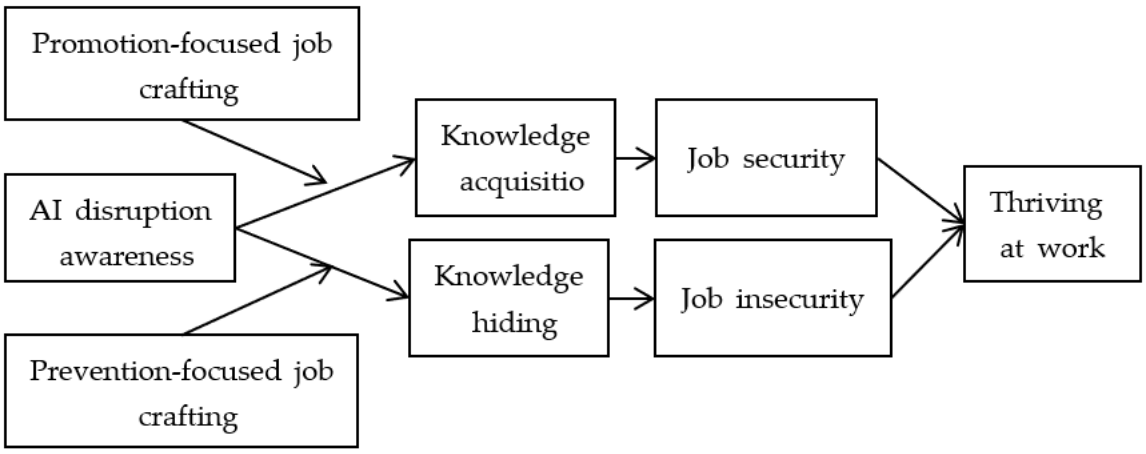


Figure 1

The dual-path theoretical model.

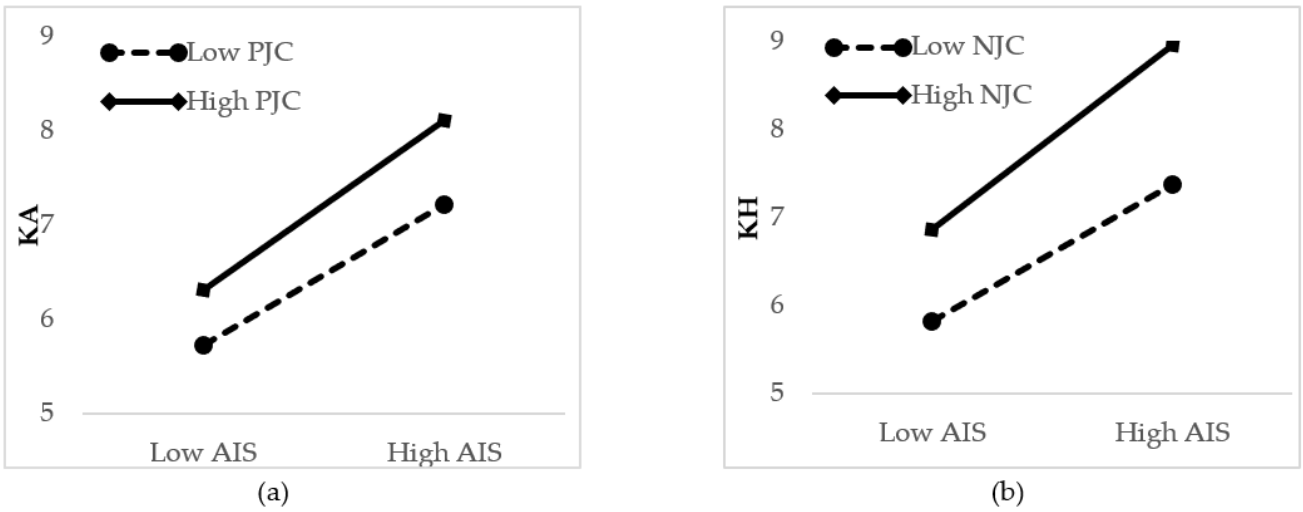


Figure 2

Moderating Effects of Job Crafting

Supplementary Files

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- QuestionnaireChinese.docx
- QuestionnaireEnglish.docx
- VariableCodebookEnglish.docx
- RawDataAnonymous.xlsx
- Eightfactor.amosoutput
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