A Study of the Double-edged Sword Effect of Organizational AI Adoption on Work Well-being of Knowledge-based Employees

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Abstract. While research and practical experience have demonstrated that organizational adoption of artificial intelligence can yield various benefits for employees, including enhanced work performance and heightened work engagement, scant consideration has been given to its influence on the work well-being of these employees. Indeed, investigating these relationships holds significant importance. This is because technological innovation aimed at enhancing human well-being is a perpetual theme. Unleashing and harnessing the potential of AI to enhance organizational operations and promote the well-being of its members constitute the prevailing value proposition for future AI adoption. Given this, based on the cognitive-affective personality systems theory (CAPS), this study constructs a double-edged sword model of organizational AI adoption on knowledge-based workers' work well-being. Specifically, this paper argues that organizational AI adoption will both enhance employees' role breadth self-efficacy, probbnnmoting work well-being (cognitive pathway), and stimulate employees' AI anxiety, inhibiting their work well-being(affective pathway). In addition, this study examined the moderating role of AI awareness impacts in these two paths. Multisource data (n = 314) from China support the proposed theoretical framework.

Keywords: Organizational AI adoption, Role breadth self-efficacy, AI anxiety, Work well-being, AI awareness.

1 Introduction

In recent years, with the booming development of Artificial Intelligence (AI) technologies such as ChatGPT, many organizations have actively embraced AI technologies [1]. Meanwhile, those organizations have achieved autonomous learning and boosted their businesses toward intelligence. For example, hospitals use AI diagnostic and treatment systems to help doctors identify and diagnose illnesses [2]; and service-oriented businesses use chatbots and virtual voice assistants to give service to their customers [3]. The results of the Resume Builder research in early 2023 show that 49% of U.S. businesses already use ChatGPT, and 30% plan to start using ChatGPT.

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It is evident that AI is playing an increasingly critical role in the way when organizations conduct their work. Organizational AI adoption refers to the intensity of the adoption of AI technology with organizations as the main body [4]. Past research on AI adoption has focused on exploring individual adoption of AI applications and functions, such as AI acceptance [5], but relatively little research has been conducted on organizational AI adoption. With the large-scale application of AI in organizations, it is necessary to go deeper to explore the corresponding psychological and behavioral impacts of organizational adoption of AI technologies on employees. At the same time, under the uncertain scenario of organizational AI adoption, knowledge-based employees have become the "main employees"[6] who collaborate with AI in organizations due to their high level, strong ability, and innovative spirit. Hence, the research object focuses on knowledge-based employees. Therefore, it is especially crucial to explore the internal influence mechanism of organizational AI adoption on knowledge-based employees.

1.1 Organizational AI Adoption

Along with the rapid application of AI in enterprise organizations, scholars have also carried out many studies on the impact of the application of AI technology in the workplace on the psychology and behavior of knowledge-based employees. Cheng et al. proposed organizational AI adoption to study the degree and frequency of the application of AI technology in organizations[7]. The higher degree of organizational AI adoption represents that the organization adopts AI more frequently and more often. For example, a higher proportion of knowledge-based employees in the organization are exposed to AI while completing most of their work tasks, or most of the work time are confronted with AI in the organization.

1.2 Cognitive Pathway of Organizational AI Adoption: Organizational AI Adoption, Role Breadth Self-efficacy, and Work Well-being

Cognitive systems provide templates for individuals when selecting and interpreting information, and profoundly influence the scope of their attention and the process of interpreting external stimuli. Role-breadth self-efficacy was first proposed by Parker [8], who argued that role-breadth self-efficacy refers to an employee's self-perception of his or her ability and confidence to take on new roles, embrace new tasks, and deal with "an integrated set of interpersonal tasks" during the work process. Role-breadth self-efficacy emphasizes self-identity at the individual level, emphasizing the cognition of "I can", which enables knowledge-based employees to obtain more cognitive resources and promotes their own positive mental activities and behavioral choices. In summary, the organizational AI adoption by knowledge-based employees exerts a synergistic effect that enhances the cognitive resources of knowledge-based employees, which in turn is prone to role-breadth self-efficacy, and ultimately leads to an increase in the well-being of knowledge-based employees at work.

1.3 Affective Pathways of Organizational AI Adoption: Organizational AI Adoption, AI Anxiety, and Work Well-being

Johnson et al. first proposed the concept of AI anxiety and defined it as an individual's fear and anxiety of losing control of AI. Wang et al. defined AI anxiety as a kind of anxiety or fear expressed in the overall emotion induced by an individual's interaction with AI, which proves the objective existentialism. AI anxiety is the AI technology application situation of the state anxiety, which usually arises when individuals face the potential threat and pressure of AI, and is a negative emotional experience. Relevant studies have shown that AI anxiety may negatively affect the emotional experience experienced by knowledge-based workers at work and the acquisition of a sense of self-fulfillment at work. Therefore, knowledge-based employees may regard organizational AI adoption as the main source of stress in AI scenarios, which triggers a negative emotional experience, and consequently, AI anxiety, leading to a decrease in the work well-being of knowledge-based employees.

1.4 The Moderating Role of AI Awareness

Some scholars have coined the term "artificial intelligence awareness" [9] to refer to this discomfort of knowledge-based employees in the digital age, which is specifically defined as the degree to which employees perceive that artificial intelligence technology poses a threat to their career development. Meanwhile, given that AI awareness is perceived differently by different knowledge-based employees, it can be regarded as a personality trait. It has been shown that knowledge-based workers with different levels of AI awareness have different perceptions, attitudes, and behavioral patterns toward the adoption of AI in their organizations. As a result, this study hypothesized that AI awareness may play a moderating role in the mechanism of action of organizational AI adoption on knowledge-based workers' role breadth self-efficacy and AI anxiety. Specifically, When there is a slight incremental change in the degree of organizational AI applied by knowledge-based workers, knowledge-based workers with high AI awareness react sensitively and strongly to organizational AI adoption in terms of cognition and affect, as evidenced by lower levels of role-breadth self-efficacy as well as increased AI anxiety.

2 Research Methods

This study collected multi-source data at two time points through several information technology firms in southeastern China. In these firms, We selected knowledge-based employees applying AI machines or technologies as the research object. We first apply Bayes' theorem for CFA test and Bayes' theorem is shown in equation(1).

$$\rho(\theta \mid \gamma) = \frac{\rho(\gamma \mid \theta)\rho(\theta)}{\rho(\chi)} \tag{1}$$

As an example, a validated factor analysis model with p measurement entries and q latent factors (p>q) is used to introduce Bayesian structural equation modeling. The validated factor analysis model is shown in Equation (2).

$$\gamma_{\mathrm{i}} = \mu + \Lambda\omega_{\mathrm{i}} + \varepsilon_{\mathrm{i},}\ \ i = 1\ldots\ \ldots n \tag{2}$$

Prior to testing our proposed hypotheses, we conducted a series of CFAs using Mplus 8.4 to assess the measurement validity of our proposed measurement model. As shown in Table 1, the results of our multilevel CFA with a five-factor measurement model.

Table 1. Results of confirmatory factor analysis

Model	χ2	df	χ2 /df	RMSEA	SRMR	CFI	TLI
Six-factor Model	517.378	188	2.752	0.075	0.141	0.925	0.907
Five-factor Model	492.176	199	2.473	0.068	0.048	0.933	0.922
Four-factor Model	1558.145	203	7.676	0.146	0.178	0.690	0.647
Three-factor Model	2172.760	206	10.547	0.174	0.205	0.550	0.496
Two-factor Model	2492.866	208	11.985	0.187	0.208	0.477	0.420
One-factor Model	3839.503	209	18.371	0.235	0.263	0.170	0.082

The mean, standard deviation, and correlations of each research variable are shown in Table 2.

Table 2. Means, standard deviation, and correlation matrix of the variables

Variable	M	SD	1	2	3	4	5	6	7	8	9
1. Gender	1.350	0.477									
2. Age	1.480	0.572	-0.388**								
3. Education	3.370	0.534	-0.183**	0.367**							
4. Tenure	1.550	0.911	-0.312**	0.735**	0.119*						
5. OAIA	3.207	1.044	0.063	-0.152**	0.060	-0.204**					
6. AIA	2.688	0.915	0.002	-0.026	-0.055	-0.042	0.139*				
7. RBSE	3.841	0.739	-0.139*	0.140*	-0.008	0.193**	0.133*	-0.106			
8. AIAN	2.883	0.925	0.026	-0.068	-0.062	-0.033	0.147**	0.481**	-0.052		
9. WB	3.571	0.803	-0.129*	0.058	0.061	0.071	0.188**	-0.199**	0.291**	-0.169**	

3 Results

Main effect test. In this study, the Mplus full model was used to test the main effect, and the results of the full model test are shown in Fig.1.

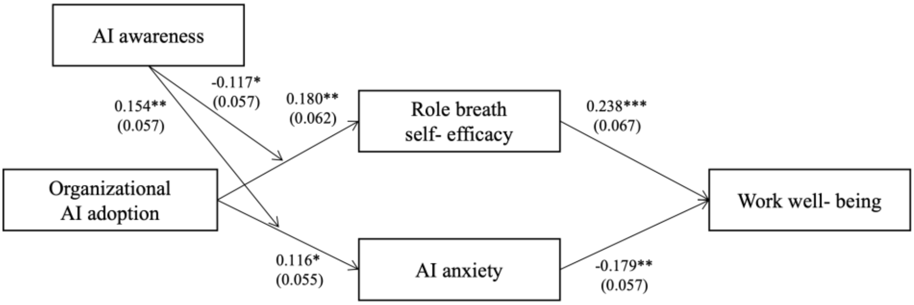

Fig. 1. Path coefficient.

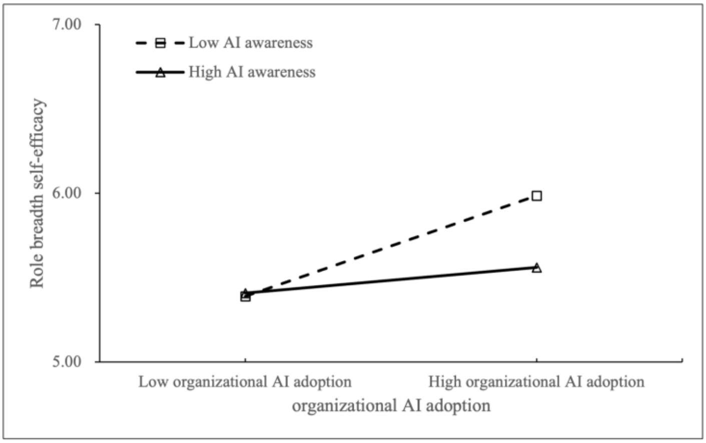

Fig. 2. Cross-level moderating effect of AI awareness on the relationship between organizational AI adoption and role breadth self-efficacy

Mediation effect test. With the help of Mplus 8.4 to analyze the path coefficient of the variables, the sampling number is 5000 times, and the results of the bootstrapping mediation effect test show that the indirect effect of organizational AI adoption on work well-being through role breadth self-efficacy is 0.043, and the 95% confidence interval is [0.012, 0.078]. The indirect effect of organizational AI adoption on work well-being via AI anxiety was -0.021 with a 95% confidence interval of [-0.049, -0.003]. The above confidence intervals do not contain 0. Moderating effect test. AI awareness negatively moderates the relationship between organizational AI adoption and role breadth self-efficacy ($\beta = -0.117$, $p < 0.05$); AI awareness positively moderates the relationship between organizational AI adoption and AI anxiety ($\beta = 0.154$, $p < 0.01$). To further test the moderating effect between AI awareness and role breadth self-efficacy and AI anxiety, referring to AIKEN et al. the moderating variables plus or minus one standard deviation were divided into high and low groups, respectively, and included in the regression model, which were regressed by interacting with the independent variables, respectively, and the graphs of the moderating effect are given in Fig.2 to Fig. 3.

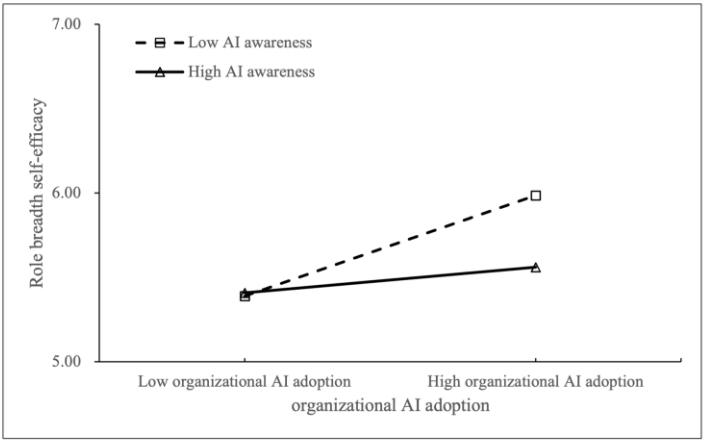

Fig. 3. Cross-level moderating effect of AI awareness on the relationship between organizational AI adoption and AI anxiety

4 Conclusion

Based on CAPS theory, this study constructs a cognitive and affective dual-path integration model of organizational AI adoption affecting knowledge-based employees' work well-being, confirms the double-edged sword effect of organizational AI adoption, and further explores the boundary conditions of positive and negative effects of organizational AI adoption by introducing AI awareness as a moderating variable.

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