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Facilitating or Inhibiting: A Cross-Level Study of the Impact of Artificial Intelligence Usage on Employees' Thriving at Work

Jianhong Tao, Yan Ke*

School of Economics & Management, Shaanxi University of Science & Technology, Xi'an, China
Email: taojianhong@sust.edu.cn, *230711036@sust.edu.cn

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Abstract

The wide application of AI in organizational management practices triggers disruptive changes in the workplace, its impact on psychological well-being remains underexplored. Therefore, based on the work requirement-resource model, this paper thoroughly studied the role mechanism of AI usage on employees' thriving at work. Through a two-stage matched questionnaire, 73 teams with a total of 461 employees were sampled, and the data were analyzed using a multi-level structural equation model. Our findings suggest that AI usage exerts a double-edged sword effect on employees' thriving at work, mediated by employees' AI perception. Additionally, digital leadership moderates these relationships across levels. Our findings reveal the mechanism and boundary conditions of AI usage affecting employees' thriving at work, and offer actionable insights for organizations to balance AI adoption with employee well-being.

Keywords

Artificial Intelligence Usage, Thriving at Work, AI Perception, Digital Leadership

1. Introduction

In the 21st century, the rapid development and wide application of intelligent technology has profoundly changed the basic form of society and is accelerating penetration in organizations. For enterprises, the introduction of Artificial Intelligence (AI) technology has not only helped them to improve operational efficiency and reduce costs, but also become an important means of assisting employees to do their work faster (Mu et al., 2023; Anthony et al., 2023). However, at the same time, the introduction of AI has also changed the way and content of business management as well as the organizational ecology (Luo et al., 2022), and profoundly reshaped the cognition, emotional state, and behavioral performance of employees (Tang et al., 2022; Gui et al., 2024). As a manifestation of employees' positive psychological state, thriving at work includes learning and vitality, which is directly and significantly related to individual performance and organizational effectiveness (Spreitzer et al., 2005). Studies have explored the effects of AI usage on employees' work performance and innovative behaviors (Heng et al., 2023; Liu et al., 2024), but these studies have focused more on employees' work performance and behavioral performance, and few studies have examined the effects of AI usage on employees' psychological states. As a result, AI usage in organizations is not only a technology adoption issue, but also a complex systematic project involving management innovation, organizational change, and employees' psychological adaptation, and the mechanism and boundary conditions of its impact on employees' mental health status need to be further explored.

The Job Demands-Resources (JD-R) model posits that jobs influence employees through two distinct pathways: the attrition path, where job demands erode employee well-being, and the gain path, where job resources enhance it. These dual paths affect employees' psychology, which in turn shapes their behavioral performance (Bakker et al., 2023). This paper argues that the JD-R model provides a comprehensive analytical framework for understanding the relationship between AI usage and employees' thriving at work. In terms of AI usage, the attrition path suggests that over-reliance on AI and the job demands arising from technological change can create maladjustment, threats, and substitution risks for employees (Basu et al., 2023). Conversely, through the gain path, AI usage provides resources for business development, enabling companies to enhance management efficiency and improve both customer and employee experiences (Chowdhury et al., 2023; Wang et al., 2024a). Therefore, this study combines the JD-R model with an integrative perspective to examine the mechanisms through which AI usage has a double-edged impact on and how it promotes and inhibits employees' thriving at work.

Indeed, employee attitudes are a key predictor of technology use (Suseno et al., 2023), and employees may hold both positive and negative attitudes toward AI in different contexts, depending on their perceptions of the costs and benefits AI brings (Kong et al., 2024; Li et al., 2019). On the one hand, AI usage can simplify cumbersome workflows, handle repetitive tasks, reduce employees' workload (Tang et al., 2022). When employees perceive AI as beneficial, they are more likely to accept and embrace its use. On the other hand, the anthropomorphic nature of AI and its advanced capabilities can also make employees feel uneasy and experience identity threats (Wang et al., 2019; Xu & Wang, 2023). The negative perceptions employees have of AI may lead them to feel averse or even resistant to it, subsequently affecting their proactive work behavior (Zhang et al., 2024). In contrast, individuals' positive perceptions can foster their realization of thriving at work

(Shi & Zheng, 2021). Therefore, this paper argues that employees' perceptions of AI shape their attitudes toward accepting or using AI technology, thereby influencing their level of thriving at work.

In the era of AI, leaders, as a vital organizational resource, significantly influence employees' attitudes and behaviors through their level of digital leadership, while also promoting organizational transformation and change (Jian & Bin, 2023; Roman et al., 2019). This influence operates not only at the macro level, affecting the organization and team, but also at the micro level, directly impacting the psychological state and behavior of individual employees (Zou et al., 2020). According to the Job Demands-Resources (JD-R) model, leaders, as key figures in employees' work environment, provide targeted resource support and shape employees' attitudes and resource utilization, which in turn affects their work outcomes (Bakker & Demerouti, 2017). Consequently, in the context of digital transformation, leaders can effectively leverage digital technologies, such as AI, to guide teams and individuals toward achieving organizational goals and encouraging proactive learning, and ultimately promoting thriving at work (Li et al., 2025).

Combining the above analyses, this paper constructs a dual-path model of how AI usage affects employees' thriving at work through their perceptions of AI, within the theoretical framework of the JD-R model. It also examines the cross-level moderating role of digital leadership, develops hypotheses, tests them empirically, and thoroughly discusses the implications for theory and practice.

2. Theoretical Analysis and Research Hypotheses

2.1. Impact of AI Usage on Employees Thriving at Work

Along with the dynamic development of AI technology, an increasing number of AI tools such as AI assistants, intelligent robots, and ChatGPT are being utilized in the workplace. For AI usage, scholars have defined it in their studies as being the extent to which employees use AI and invest time and effort in pursuing work goals and accomplishing work tasks (Mu et al., 2023), as well as the degree to which individuals accept the behaviors and intentions of AI (Li et al., 2023; Rathi et al., 2024). Employees with higher levels of AI usage report relying on AI for most of their work tasks or spending the majority of their work time using AI (Tang et al., 2022). In contrast, thriving at work is a positive psychological state in which an individual grows and develops professionally, encompassing the dimensions of learning and vigor (Spreitzer et al., 2005). According to the social embeddedness model of thriving at work, it is not a static state but a dynamic and evolving process, influenced by changes in organizational contextual features and resources (Spreitzer et al., 2005; Han et al., 2022). Based on the JD-R model, job resources can provide resource support to individuals and motivate personal growth and development. In contrast, job demands, which are the continuous efforts of employees to accomplish tasks, deplete individuals' physical and mental resources and have a negative impact on employees (Demerouti et al., 2001).

Based on this, this study concludes that AI usage has both positive and negative effects on employees' thriving at work.

Specifically, on the one hand, this study argues that AI usage brings work resources to employees that can energize them and promote thriving at work. For example, As AI possesses the capability to automate task processing, it can independently take over routine duties associated with employee roles, thereby substituting human labor in performing tedious, dirty, hazardous, or dangerous work (Huang et al., 2024). This contributes to an improved working environment and enhances employees' mental well-being. Simultaneously, in the workplace, AI can serve as a creative support partner by providing data and content assistance. Through such AI-human collaboration, work efficiency can be significantly enhanced, along with an increased sense of work-related self-efficacy (Sheng et al., 2022; Lin & Zhu, 2025). Employees are more likely to develop trust in AI (Cheng et al., 2023) and are willing to proactively use AI to improve work efficiency and promote work prosperity.

On the other hand, AI usage brings new work requirements, which easily triggers employees' uneasy emotions and negative reactions, and is not conducive to employees' thriving at work. It has been shown that AI usage changes the original work content, habits, and methods of organizational employees, which is prone to cause technological anxiety, insecurity, and even panic (Guo & Wei, 2024; He et al., 2023), and triggers the fear of job replacement (Yam et al., 2023). Meanwhile, AI usage also brings new job requirements, forcing employees to continuously learn new knowledge and job skills to adapt to the rapidly changing smart work environment. In this process, employees have to deplete more resources and energy (Bakker & De Vries, 2021), which to some extent impairs employees' work autonomy, increases their workload (Jia et al., 2024), brings unpleasant work experiences, and even prompts a series of negative behaviors and reactions such as emotional exhaustion and job burnout (Yin et al., 2024), which is not conducive to employees' thriving at work. From a positive technical perspective, high job demands can also act as motivators, with some employees viewing them as opportunities for personal growth and development (Ding, 2021).

2.2. The Mediating Role of AI Perception

AI perceptions refer to employees' perceptions of how AI usage affects their work attitudes, behaviors, well-being, and work environment (Wang et al., 2024a). Studies have shown that when employees perceive AI as useful and easy to use, the likelihood of their acceptance and usage of AI increases (Baabdullah et al., 2021; Cheng & Wu, 2023) making it easier for them to develop a positive perception of AI. Conversely, AI's shortcomings can lead employees to form negative perceptions and exhibit resistance to AI (Parvez et al., 2022). Meanwhile, the JD-R model suggests that, under the same job characteristics, employees develop different perceptions of their job requirements and resources (Bakker &

Demerouti, 2007). However, the use of digital technologies such as AI significantly alters employees' job characteristics, disrupting the traditional balance between job requirements and resources. AI reshapes employees' perceptions of these requirements and resources. Furthermore, employees' own perceptions can, in turn, profoundly influence their subsequent psychological states and work behaviors (Wang et al., 2024a). Therefore, this paper argues that AI usage can affect employees' work status and behavior by influencing their perceptions of AI-related resources or requirements, leading to the proposed research hypothesis H1.

H1: *AI perception plays a mediating role between AI usage and employees' thriving at work.*

To be specific, the transmission mechanisms through which AI perceptions play a mediating role can be categorized into two aspects: one is that AI usage promotes employees' thriving at work through positive AI perceptions, and the other is that AI usage inhibits employees' thriving at work through negative AI perceptions. The specific analysis is as follows:

The JD-R model proposes that work resources themselves have motivational potential that promotes positive perceptions and significantly enhances individuals' positive mental states and stimulates creative work behaviors (Demerouti et al., 2001; Wu & Sun, 2025). Specifically, AI technology provides employees with more work-related supportive resources, such as AI-driven intelligent decision-making tools, data analysis suggestions, etc., which help employees to automate and be efficient in the office. And AI can quickly capture, mine, and independently analyze and process data (Raisch & Krakowski, 2021), providing employees with valuable information (Tang et al., 2022), which helps to reduce employees' cognitive load and work pressure, and bring employees a positive psychological experience (Heng et al., 2023). AI usage also improves employees' work flexibility and autonomy, enabling employees to go for creative and personalized work services (Jia et al., 2024), stimulating employees' work vitality and passion, and promoting employees' career development (Huang et al., 2024). Employees are prone to acquire positive emotions such as support and ability enhancement in the process of interacting with intelligent machines, which in turn makes them more trustful and fully utilize AI technology to serve themselves, and more likely to reach thriving at work. As a result, the work resources brought by AI usage will prompt employees to have positive perceptions of it, which will help promote individuals thriving at work. Accordingly, the paper proposes the following hypothesis:

H1a: *AI usage enhances thriving at work via positive AI perceptions.*

The JD-R model posits that job requirements negatively impact employees, suggesting that high job demands trigger negative perceptions, resulting in adverse behaviors such as emotional exhaustion and burnout (Bakker et al., 2023). Specifically, AI usage has transformed organizational work environments and increased employee job skill requirements, and employees need to make continuous efforts to adapt to the new work environment of human-computer collaboration (Einola & Khoreva, 2023; Wang et al., 2022), such as job training and skill enhancement training, etc., whereas excessive requirements and training will increase employees' cognitive load and psychological pressure, which in turn continues to reduce employees' work vigor and impair their physical and mental health (Meng & Xu, 2024). It has been shown that employees' perceived high job demands also reduce individuals' job satisfaction and vigor, which in turn reduces work engagement and even produces job burnout (Kong et al., 2024). In addition, AI also causes employees to develop a job replacement crisis (Li et al., 2019), which is prone to negative cognitions and emotions such as anxiety and depression, and further affects their performance and job creativity (Liang et al., 2022; Tan & Xin, 2025). Therefore employees' negative perception of AI may make them develop negative work psychology and behavior due to the continuous depletion of resources, inhibiting them from thriving at work. Accordingly, the paper proposes the following hypothesis:

H1b: *AI usage inhibits thriving at work via negative AI perceptions.*

2.3. The Moderating Role of Digital Leadership

Based on the JD-R model, leaders, as key figures in an employee's work environment, affect employees' attitudes and use of resources, which in turn influence their work outcomes (Bakker & Demerouti, 2017). Digital leadership is a leadership style that has emerged alongside enterprise digital transformation. It involves leaders using advanced AI technology to influence individuals, groups, and organizations in terms of attitudes, perceptions, and behaviors (Roman et al., 2019). It also encompasses the intellectual ability and literacy that leaders should possess in the digital era (Jäckli and Meier, 2020). In digital contexts, leaders are change-oriented, interacting with followers and their teams by managing the digital environment, leveraging digital tools, and providing technical guidance and resource support to employees (Wang et al., 2024b). Numerous studies have shown that leaders not only significantly impact organizational and team development but also shape the cognitive attitudes of individual employees (Liu et al., 2024). Therefore, leaders with a high level of digital leadership can actively adapt to and drive organizational change, clarify the strategic goals and processes of transformation, and fully utilize AI technology to provide assistance and support for employees. This promotes better acceptance of and identification with AI, thereby influencing employees' subsequent work status and behavior.

On one hand, the introduction of enterprise AI facilitates organizational change, and leaders with a high level of digital leadership can quickly adapt to this change and clearly explain the value that intelligent technology brings to the organization and its employees (Ke, 2020). This helps employees perceive the positive impacts of AI and alleviates their concerns about AI more quickly. On the other hand, AI usage introduces technological threats and job insecurity for employees, and those in such an environment may develop an aversion to or even resistance toward AI

(Zhang et al., 2024). In such environments, leaders with a high level of digital leadership pay attention to their employees' mental health and positively guide them to accurately assess the value of AI. This reduces employees' resistance to AI and helps them recognize its convenience. Meanwhile, leaders with strong digital leadership also focus on the long-term development of their employees, providing support such as technical guidance and humanistic care. They also set an example for their employees through their own actions (Zhu & Yu, 2024), which enhances employees' recognition of AI usage. Accordingly, this paper proposes the following hypotheses:

H2a: *Digital leadership plays a cross-level moderating role between AI usage and positive AI perceptions, i.e., the higher the level of digital leadership, the stronger the positive impact of AI usage on positive AI perceptions.*

H2b: *Digital leadership plays a cross-level moderating role between AI usage and negative AI perceptions. i.e., the higher the level of digital leadership, the weaker the positive effect of AI usage on negative AI perceptions.*

Furthermore, leaders with a high level of digital leadership prioritize the cultivation and enhancement of their employees' digital competence (Li & Miao, 2020). They fully utilize AI technology to create a favorable working environment for their employees, providing technical guidance and resource support. The positive guidance from these leaders can activate a positive psychological state in team members (Li & Mao, 2018). When employees experience this guidance and support, it not only enhances their perception of AI's positive aspects but also, based on their own psychological feedback, encourages them to proactively use the resources provided by AI. This, in turn, improves work efficiency, helps achieve work goals, and promotes thriving at work. Meanwhile, leaders with high levels of digital leadership actively monitor the impact of AI-driven work environments on employees' psychology and behavior. They proactively provide resources to buffer potential negative effects of AI usage while reinforcing its positive impacts (Lin et al., 2024). In contrast, leaders with a low level of digital leadership lack certain competencies, making it difficult for them to offer support to alleviate employees' technological anxiety and job insecurity. This can further exacerbate employees' negative perceptions of AI, which in turn diminishes their vigor and passion for work and hinders their ability to thrive at work. In light of this, the paper argues that digital leadership influences the mediating effect of employees' AI perceptions in the relationship between AI usage and employees' thriving at work. Accordingly, this paper proposes the following hypotheses:

H3a: *The higher the level of digital leadership, the stronger the indirect effect of positive AI perceptions of employees, i.e., the stronger the cross-level impact of AI usage on employees' thriving at work through positive AI perceptions.*

H3b: *The higher the level of digital leadership, the weaker the indirect effect of negative employee AI perceptions, i.e., the weaker the cross-level impact of AI usage on employee thriving at work through negative AI perceptions.*

In conclusion, this paper constructs the theoretical model **Figure 1**.

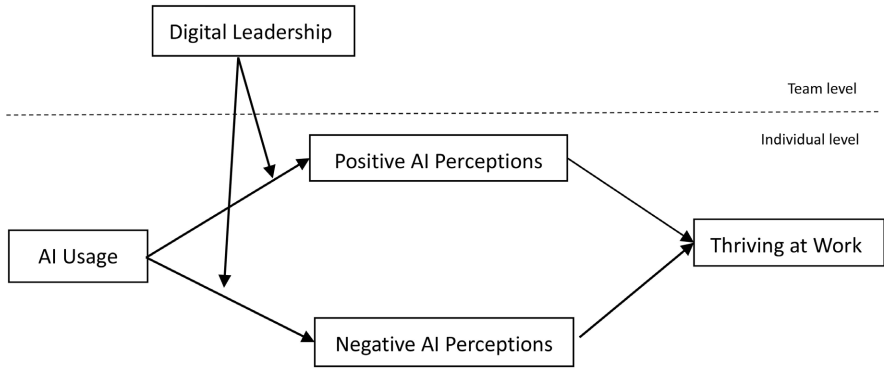

Figure 1. Theoretical model.

3. Research Design

3.1. Research Sample and Data Collection

This study selects enterprise managers and employees in IT, manufacturing, healthcare, media, and education industries as research subjects. These industries are typically AI-intensive, and their daily operation management and organizational communication are deeply integrated with AI technologies. To enhance data quality and reduce the impact of common bias, the study collected data in two phases with a one-month interval. During the research process, we contacted the managers and human resource directors of the participating companies in advance, explained the research purpose, obtained their support, and then collaborated with the human resource directors to determine the list of team members who would participate in the study. Before initiating the formal investigation, to ensure that research participants accurately understood the context of AI usage in the workplace, we followed the approach of scholars Tang et al. (2022). Participants were pre-sensitized with a briefing on AI tools, such as Chat GPT, and their workplace applications, providing them with a clear understanding of the AI usage context before proceeding to the formal question-and-answer session.

In the data collection phase, the first stage invited all participating employees to provide demographic information about themselves, as well as to evaluate AI usage and the digital leadership of their supervisors. In this phase, 600 questionnaires were distributed, and 548 were collected after screening and removing invalid responses. In the second phase, questionnaires were distributed via email to the 546 employees and their team leaders who had participated in the previous round, inviting employees to assess their AI perceptions and leaders to evaluate employee thriving at work and related demographic information. After completing the survey, 87 teams and 504 employee questionnaires were collected by matching them to identification numbers. Following further screening to eliminate unqualified responses, 73 teams and 461 valid employee questionnaires were obtained, yielding validity rates of 76.83%. Among the respondents, men accounted for 44.03% and women for 55.97%. Employee ages were primarily concentrated in the under-25 and 26 - 35 age groups, representing 52.28% and

32.75%, respectively. Education levels were mainly bachelor's degrees and master's degrees or higher, accounting for 44.9% and 47.29%, respectively. The average work experience was 5.5 years. In terms of position levels, grassroots employees comprised 62.04%, grassroots managers 25.81%, and middle and senior managers 12.15%.

3.2. Variable Measurement

Variable measurements were selected from mature scales validated by scholars both domestically and internationally. All scales were scored on a 5-point Likert scale.

AI Usage. A three-item scale adapted from Tang et al. (2022) was used, with items such as "I spend most of my time working with AI." Higher scores indicate greater AI usage. The Cronbach's alpha coefficient for this scale was 0.913.

AI Perception. The scale developed by Park et al. (2024) was selected. Positive AI perception items include "I feel that AI works reliably at work," while negative AI perception items include "AI usage at work is a bit daunting for me." The Cronbach's alpha coefficient for the scale was 0.877, with coefficients of 0.938 for positive AI perception and 0.969 for negative AI perception.

Digital Leadership. A six-item scale developed by Zeike et al. (2019) was used, with items such as "My supervisor thinks it is fun to use digital tools." The Cronbach's alpha coefficient for this scale was 0.948.

Thriving at Work. The scale developed by Porath et al. (2012) was used, comprising two dimensions learning and vigor—with eight items, such as "I feel energized and refreshed at work." The Cronbach's alpha coefficient for this scale was 0.963.

Control Variables. Gender, age, education, years of experience, and occupational level of employees were selected as control variables in this study. An individual's acceptance of technology is significantly correlated with gender and age (Cheng et al., 2023). As a new digital technology, AI is rapidly transforming various fields and reshaping employees' cognitive thinking and work environments. The education of individual employees and leaders, along with their career level, influences the acceptance and adaptability of the technology. Meanwhile, employees with more years of experience are better adapted to corporate culture and thus more likely to understand the reasons for introducing AI in the company, making them more inclined to proactively utilize AI technology to improve work efficiency.

4. Results

4.1. Common Methodological Biases

Although this study employed multi-stage surveys and anonymous measurements to reduce the effects of common method bias, further statistical tests of the measurement data are necessary. First, the data were analyzed using Harman's single-factor method. After unrotated principal component analysis, the first factor explained 32.985% of the variance, which did not exceed 40%. Next, this study conducted confirmatory factor analysis using Mplus 8.3. Given that the limited sample size and the large number of items in the variables could affect model fit, variables with numerous items (e.g., AI perception) were parceled to improve fit before conducting the confirmatory factor analysis. Specifically, the study first performed a factor analysis to rank the factor loadings of the question items in descending order. Then, the items were grouped by alternating high and low loadings to minimize intergroup differences (Wu & Wen, 2011). The results of this analysis are presented in **Table 1**, which shows that the five-factor model provided the best fit (χ^2/df = 2.740, RMSEA = 0.061, CFI = 0.980, TLI = 0.974, SRMR = 0.028). This fit is significantly better than that of the other models in comparison, indicating good discriminant validity among the variables.

Table 1. Validation factor analysis results.

Model	X^2	df	X^2/df	CFI	TLI	RMSEA	SRMR
Five-factor model: AIU, DL, PP, NP, TW	219.209	80	2.740	0.980	0.974	0.061	0.028
Four-factor model: AIU + DL, PP, NP, TW	1134.221	84	13.502	0.851	0.814	0.165	0.142
Three-factor model: AIU + DL, PP + NP, TW	2737.341	87	31.464	0.625	0.547	0.257	0.176
Two-factor model: AIU + DL, PP + NP + TW	4472.616	89	50.254	0.379	0.268	0.327	0.244
One-factor model: AIU + DL + PP + NP + TW	5068.593	90	56.318	0.295	0.177	0.346	0.209

Note: "+" represents two factors combined into one, AIU for AI usage, DL for digital leadership, PP for positive AI perception, NP for negative AI perception, and TW for employees thriving at work.

4.2. Data Aggregation Analysis

Digital leadership is a team-level variable, but its actual measurement is based on employee evaluations. To determine whether individual-level data are suitable for aggregation to the team level, the relevant aggregation indices need to be calculated. After calculation, the mean Rwg value for digital leadership was 0.74 (>0.7), indicating that the digital leadership scores of the 73 team leaders exhibit high intra-group consistency. Meanwhile, the ICC(1) value was 0.25 (>0.05), and the ICC(2) value was 0.68 (>0.5), suggesting a high degree of inter-group variability in the data. Taken together, these results indicate that the variable is suitable for cross-level analysis (Bliese, 1998).

4.3. Descriptive Statistics and Correlation Analysis

The descriptive statistics and correlation analysis of the variables are presented in **Table 2**. The results show that AI usage is significantly and positively correlated with both positive and negative AI perceptions of employees (r = 0.256, $p < 0.01$; r = 0.201, $p < 0.01$). Positive AI perceptions of employees are significantly and positively correlated with thriving at work (r = 0.306, $p < 0.01$), while negative AI perceptions of employees are significantly and negatively correlated with thriving at work (r = −0.235, $p < 0.01$).

Table 2. Descriptive statistics and correlation coefficients of the variables.

Variables	M	SD	1	2	3	4	5	6	7	8	9
1 Genders	0.56	0.497	—								
2 Age	1.66	0.800	−0.137**	—							
3 Qualifications	2.39	0.629	0.112*	−0.018	—						
4 Work Experience	1.76	0.994	−0.140**	0.708**	−0.174**	—					
5 Career level	1.50	0.703	−0.101*	0.455**	0.019	0.441**	—				
6 AIU	3.19	1.211	0.057	0.038	0.043	−0.069	0.064	—			
7 PP	3.63	0.939	0.018	0.155**	−0.046	0.092*	0.117*	0.256**	—		
8 NP	2.66	1.241	0.033	−0.059	0.041	−0.020	−0.004	0.201**	−0.090	—	
9 TW	3.54	1.165	−0.032	0.025	−0.036	−0.019	0.090	0.227**	0.306**	−0.235**	—
10 DG	2.70	1.268	0.025	0.105*	−0.064	0.043	0.067	0.271**	0.518**	−0.083	0.419**

Note: $^{**}p < 0.01$, $^{*}p < 0.05$. AIU for AI usage, DL for digital leadership, PP for positive AI perception, NP for negative AI perception, and TW for employees thriving at work.

4.4. Hypothesis Test

4.4.1. Mediated Effect Test

In this study, Mplus 8.3 software was used to test each hypothesis through structural equation modeling. The results of the analysis and path coefficients are presented in Figure 2. The findings indicate that AI usage positively affects employees' positive AI perceptions (r = 0.269, $p < 0.001$), and employees' positive AI perceptions significantly and positively influence their thriving at work (r = 0.254, $p < 0.001$). Meanwhile, AI usage positively affects employees' negative AI perceptions (r = 0.174, $p < 0.01$), while employees' negative AI perceptions significantly and negatively impact their thriving at work (r = −0.184, $p < 0.001$).

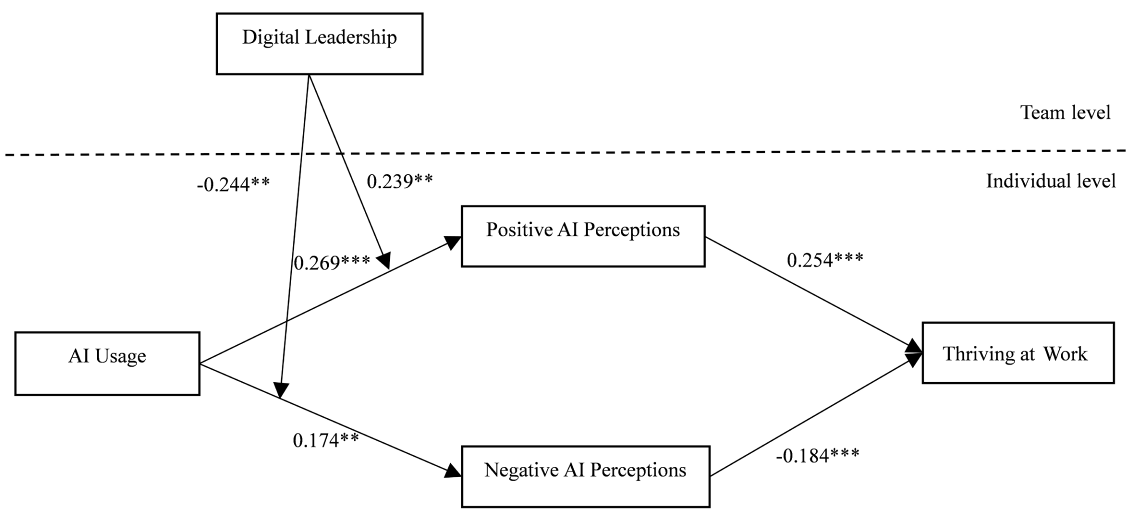

Figure 2. Path coefficients.

The mediating effect was further examined using the Monte Carlo simulation method, a statistical technique employed to estimate the potential outcomes of uncertain events. The results of these analyses are presented in Table 3. As shown in Table 3, the mediating effect of employees' positive AI perceptions between AI usage and thriving at work is 0.068, with a 95% confidence interval of [0.029, 0.115], which does not include 0. Therefore, Hypothesis H1a is supported. Similarly, the results indicate that the mediating effect of employees' negative AI perceptions between AI usage and thriving at work is −0.032, with a 95% confidence interval of [−0.064, −0.008], which also does not include 0. Thus, Hypothesis H1b is supported.

Table 3. Results of the analysis of intermediation effects.

Pathway	Efficacy value	SE	95% Confidence Interval
AIU → PP → JP	0.068	0.022	[0.029, 0.117]
AIU → NP → JP	−0.032	0.014	[−0.064, −0.008]

4.4.2. Cross-Level Moderating Effects Test

The cross-level moderating effect analysis began by centering the variables involved, constructing an interaction term between AI usage and digital leadership, and including it in the model. The results showed that the interaction term of AI usage and digital leadership positively affected employees' positive AI perceptions (r = 0.239, $p < 0.01$), indicating that digital leadership plays a positive moderating role between AI usage and employees' positive AI perceptions. In other words, the higher the level of digital leadership, the stronger the positive effect of AI usage on employees' positive AI perceptions, supporting Hypothesis H2a.

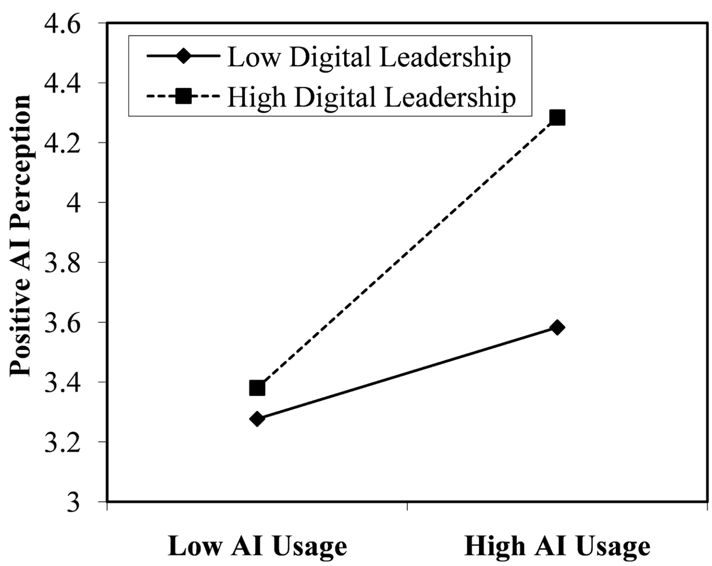

Figure 3. The moderating effect of digital leadership on the relationship between AI use and positive AI perception.

In addition, the interaction term of AI usage and digital leadership negatively affected employees' negative AI perceptions (r = −0.244, $p < 0.05$), indicating that digital leadership plays a negative moderating role between AI usage and employees' negative AI perceptions. That is, the higher the level of digital leadership, the weaker the positive effect of AI usage on employees' negative AI perceptions, thus supporting Hypothesis H2b.

Furthermore, the moderating variables were examined at high (+1 SD) and low (−1 SD) levels, and the moderating effects were plotted. As shown in Figure 3, compared to low-level digital leadership, the positive impact of AI usage on employees' positive AI perceptions is more significant under high-level digital leadership.

Figure 4 shows the moderating effect of digital leadership on the relationship between AI use and negative AI perception in the high-level digital leadership context compared to the low-level digital leadership context, the weaker the positive effect of AI use on negative AI perception.

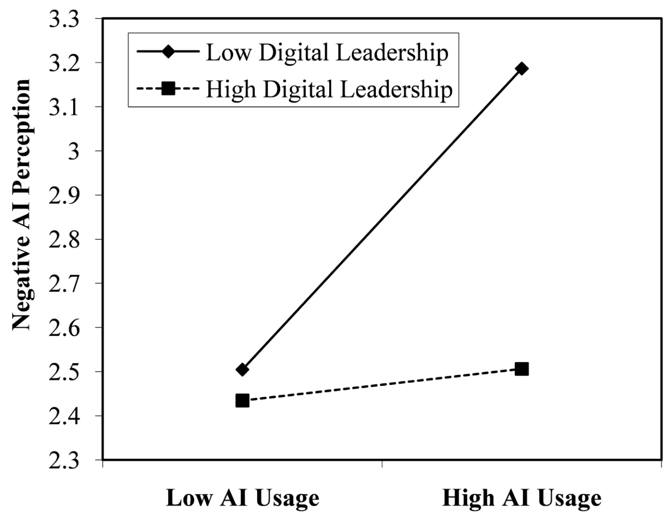

Figure 4. The moderating effect of digital leadership on the relationship between AI use and negative AI perception.

4.4.3. Moderated Cross-Level Mediation Effects Test

This study further employed the Monte Carlo method to test the moderated cross-level mediation effect of digital leadership. The results of the specific analysis are presented in Table 4. The findings indicate that, in the positive AI perception path, the mediation effect of AI usage on employees' thriving at work through positive AI perception is significant when the level of digital leadership is high ($r = 0.105$, $SE = 0.035$), with a 95% confidence interval of [0.041, 0.180], which does not include 0. However, when the level of digital leadership is low, the 95% confidence interval is [−0.009, 0.084], which includes 0, indicating that the mediation effect is not significant ($r = 0.034$, $SE = 0.021$). Moreover, the moderated mediation effect of employees' positive AI perception significantly differs between high and low levels of digital leadership ($r = 0.071$, $SE = 0.033$), with a 95% confidence interval of [0.016, 0.146], which does not include 0. Thus, Hypothesis H3a was supported.

In the negative AI perception path, when the level of digital leadership is high, the 95% confidence interval is [−0.034, 0.023], which includes 0, indicating a non-significant mediation effect (r = −0.004, SE = 0.014). In contrast, when the level of digital leadership is low, the 95% confidence interval is [−0.098, −0.015], which does not include 0, indicating a significant mediation effect (r = −0.051, SE = 0.021). Additionally, the moderated mediation effect of employees' negative AI perception significantly differs between high and low levels of digital leadership (r = 0.046, SE = 0.025), with a 95% confidence interval of [0.006, 0.103], which does not include 0. Thus, Hypothesis H3b was supported.

Table 4. Results of moderated mediation effect analysis.

Mediated Path	Digital Leadership	Efficacy Value	SE	95% Confidence Interval	
				Lower Limit	Upper Limit
AIU → PP → JP	high (+1 SD)	0.105	0.035	0.041	0.180
	low (−1 SD)	0.034	0.021	−0.009	0.084
	difference	0.071	0.033	0.016	0.146
AIU → NP → JP	high (+1 SD)	−0.004	0.014	−0.034	0.023
	low (−1 SD)	−0.051	0.021	−0.098	−0.015
	difference	0.046	0.025	0.006	0.103

5. Conclusion

Based on the Job Demands-Resources model, this study examined the mechanism through which AI usage impacts employees' thriving at work. It explored the mediating role of AI perceptions and the cross-level moderating role of digital leadership, and arrived at the following conclusions through empirical testing:

First, AI usage has a double-edged impact on employee thriving at work. From the gain path, workplace AI usage can provide convenience and additional work resources for employees, thereby promoting their thriving at work. From the loss path, AI usage can alter the work environment, and the new work demands and potential overuse of AI technology may create insecurity and work pressure. This pressure can force employees to upgrade their skills to proactively adapt to change, thereby inhibiting their ability to thrive at work.

Second, employees' AI perception plays a mediating role between AI usage and thriving at work. AI significantly influences employees' psychological perceptions and behaviors. When employees perceive that AI enhances benefits and resources, they are more likely to proactively embrace it, thereby improving their thriving at work. Conversely, when employees perceive that AI usage leads to resource depletion, they may resist it, which can hinder their thriving. Therefore, AI usage affects employees' thriving at work through the mediating role of AI perception.

Third, digital leadership cross-level moderates both the relationship between AI usage and AI perceptions and the mediating effect of AI usage on thriving at work through AI perceptions. A higher level of digital leadership enhances leaders' ability to regulate and manage AI usage in the workplace. Specifically, digital leadership can strengthen the positive effects of AI usage on employees' positive AI perceptions, as well as the mediating effect of those perceptions on thriving at work. Simultaneously, digital leadership can weaken the positive effects of AI usage on employees' negative AI perceptions and the corresponding mediating effect on thriving at work.

6. Discussion

6.1. Theoretical Contributions

First, the study verified the double-edged sword effect of AI usage and constructed a dual-path model illustrating how AI usage affects employees' thriving at work through AI perception, in conjunction with the Job Demands-Resources model. This enriches the contextual understanding of factors influencing thriving at work. Scholars have called for the exploration of the double-edged sword effect of AI from an integrated perspective (Luo et al., 2022; Jiang et al., 2024), and although some studies have comprehensively analyzed the psychological and behavioral impact of AI usage from the perspectives of resources, stress perception, etc. (Liu et al., 2024; Tan & Wang, 2025), few have focused on two key factors: the external situational feature AI usage—and the internal individual feature AI perception. These are crucial in understanding the mechanisms that drive employees' thriving at work. Examining these factors helps uncover how different workplace contexts influence employee psychology and behavior, offering micro-level insights into human-AI collaboration.

Second, the study introduces the team-level situational factor of digital leadership as a moderating variable, thereby broadening the boundary conditions for the impact of AI usage on employees' thriving at work. Most existing studies examining the boundary effects of AI focus on individual-level characteristics, such as learning goal orientation, sense of responsibility, and proactive personality (Heng et al., 2023; Zou et al., 2023). However, fewer have investigated the boundary effects of leadership or other cross-level factors. By introducing digital leadership as a contextual variable, this study responds to calls from scholars to expand research on cross-level influences in AI-related contexts (Gui et al., 2024; Tan & Xin, 2025; Han et al., 2024). The empirical results further demonstrate that the impact of AI usage on employees' AI perceptions—and the resulting influence on their thriving at work—varies according to the digital competence level of the leader. This study not only expands the boundary mechanisms of AI usage but also contributes to the growing body of research on digital leadership and its influence on individual employee behavior, confirming the cross-level moderating role of leadership in the context of AI usage.

6.2. Management Implications

First, enterprises should guide employees in the rational use of AI and pay attention to their mental health. Organizations should help employees develop a balanced view of AI's impact by providing the necessary training to ensure they can effectively utilize AI tools. This will foster positive perceptions of AI. At the same time, enterprises should value employee participation and feedback, encourage involvement in AI application and decision-making processes, and enhance work engagement and satisfaction. Additionally, companies need to pay attention to the mental health of their employees, emphasize their acceptance and emotional response to AI, and help them channel their negative emotions in a timely manner to reduce AI resistance.

Second, enterprises should invest in developing the digital leadership skills of their managers and leaders. Organizations should design targeted training programs for different management levels and encourage leaders to regularly participate in courses on digital technology and management to keep their digital knowledge up to date. Leaders must also adapt to the evolving smart era, enhance their and their teams' agility in using new technologies, and serve as role models for innovation. Furthermore, leaders should be equipped to identify and manage the risks associated with digital technologies such as data security, privacy, and over-reliance on automation—and implement safeguards to ensure their teams can respond effectively. Importantly, leaders should guide employees to avoid excessive dependence on AI, which can diminish critical thinking and creativity.

6.3. Limitations and Future Directions

There are still some limitations, mainly in the following three aspects: First, this study operationalizes AI use into duration and intensity of usage, and we also recognize that the type of AI (e.g., automated tasks vs. providing creative support) may moderate and influence the findings. However, because this study focuses on the intensity of use behavior and its overall impact, no distinction is made between types of use. Based on this, future research can further explore the impact of different types of usage.

Second, while this study confirms the double-edged sword effect of workplace AI usage on employees' thriving at work using the Job Demands-Resources (JD-R) model, it does not fully explore the motivational effects of high job demands. Therefore, future research should investigate the potential positive outcomes of job demands, explore how they may counterbalance the negative effects of AI usage, and expand the application and interpretation of the JD-R model.

Third, this study only examined the cross-level moderating effect of digital leadership, a team-level variable, on the relationship between AI usage and employee-level outcomes. However, other multi-level factors may also influence employees' thriving at work. Focusing solely on digital leadership as a moderator does not fully capture its unique or indispensable role. Future research could extend the investigation to other leadership styles and organizational-level contextual factors, such as organizational AI strategic orientation and organizational AI readiness (Zhou et al., 2025). At the same time, the study also suggests that several unmeasured latent and composite factors. For instance, individuals' digital self-efficacy, personality traits, and career stage (Xie et al., 2025), may shape their perceptions of AI technology.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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