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Impact of Different Employee–AI Interaction: Instrumental vs. Emotional Support and Gender Differences

Jiaying Chen[a], Jiaxin Xue[a], Yuhui Li[a], and Wenhao Luo[b]

[a]School of Labor and Human Resources, Renmin University of China, Beijing, China; [b]School of Economics and Management, North China University of Technology, Beijing, China

ABSTRACT

Previous studies have shown that employee–AI interactions increase job insecurity and negative behaviors, mainly due to AI's focus on task assistance while neglecting its role in emotional support. We categorize employee–AI interactions into two types: using AI for emotional support and using AI for instrumental support. We further differentiate their impact on job insecurity and knowledge hiding. Results from a multi-wave survey involving 495 participants showed that using AI for instrumental support increases job insecurity, subsequently leading to knowledge hiding, while using AI for emotional support reduces these detrimental effects. Furthermore, the mitigating effect of emotional support on job insecurity and knowledge hiding is more pronounced for women than men. No gender differences were found in the impact of instrumental support. Our study contributes to the human–AI interaction literature by exploring how the nature of AI interactions influences workplace behavior.

KEYWORDS

Artificial intelligence; instrumental support; emotional support; job insecurity; knowledge hiding; gender difference

1. Introduction

Human–AI interaction in organizations has significantly enhanced workplace productivity by supporting employees in tasks such as data analysis, document writing, and decision-making (Kanitz et al., 2023; Noy & Zhang, 2023; Radonjić et al., 2024). It has been found that AI can already free up 60–70% of work time, with estimates suggesting that half of activities could be automated between 2030 and 2060 (Chui et al., 2023). However, the powerful AI in the workplace has also made employees feel threatened (Presbitero & Teng-Calleja, 2023; Yam et al., 2023). The emergence of AI has altered work structures, prompting uncertainty regarding whether employees' competency will align with future job demands or be supplanted, which evoke employees' job insecurity and deviant behaviors (Arias-Pérez & Vélez-Jaramillo, 2022; Innocenti & Golin, 2022; Presbitero & Teng-Calleja, 2023; Yam et al., 2023).

While existing studies extensively discuss the insecurity that AI might bring, most of them focus on the role of AI in task processing. Specifically, AI is capable of solving and completing tasks that require human thinking, which can replace human employees and thus cause insecurity (Arias-Pérez & Vélez-Jaramillo, 2022; Presbitero & Teng-Calleja, 2023). However, the scope of human–AI interaction has expanded beyond task-related activities to include emotional interactions (Brandtzaeg et al., 2022; Ki et al., 2020; Lv et al., 2022; Pauw et al., 2022). AI can now express empathy, provide reassurance, and offer care, thereby delivering emotional support (Meng & Dai, 2021; Morris et al., 2018; Song et al., 2022). For example, many multi-modal AI models equipped with emotional capabilities, such as Project Astra and OpenAI's GPT-4, can engage in emotional communication. AI chatbots like Woebot and Replika are specifically designed to support mental health and provide virtual companionship (Meng & Dai, 2021; Miner et al., 2017). Moreover, a growing number of organizations are implementing AI model-based health platforms to offer psychological counseling and emotional support to employees. Despite AI's remarkable evolution in providing emotional support, current organizational research on human–AI interaction predominantly assumes that employees interact with AI solely for instrumental purpose, overlooking the scenario of interacting with AI for emotional support. This limited focus may confound the influences of AI usage on employees' psychology and behavior, biasing the understanding of its role in the workplace.

Therefore, our aim is to differentiate between instrumental and emotional scenarios of human-AI interactions and examine whether the distinct nature of human–AI interactions yields different outcomes. Drawing from the transactional theory of stress, we posit that employees' appraisal of whether AI poses a threat differs under two different usage scenarios. Specifically, the task functions of AI overlap with employees' knowledge, skills and abilities, making it possible to replace their roles at work. Consequently, employees may feel threatened when using AI for instrumental support, leading to job insecurity and triggering coping mechanisms

CONTACT Yuhui Li yuhui_li@ruc.edu.cn School of Labor and Human Resources, Renmin University of China, 59 Zhongguancun Street, Haidian District, Beijing, 100872, China

(i.e., knowledge hiding) (Arias-Pérez & Vélez-Jaramillo, 2022; Presbitero & Teng-Calleja, 2023). Conversely, the emotional capabilities of AI do not typically replace employees' human capital nor threaten their roles in competing tasks. Instead, when facing uncertainties and challenges, emotional support from AI provides employees with additional resources to alleviate stress (Mathieu et al., 2019; Pauw et al., 2022). Therefore, using AI for emotional support may potentially mitigate job insecurity and reduce knowledge-hiding.

We further examine gender differences in how AI threats or reassures employees because men and women exhibit distinct orientations towards task-related and affective aspects. Men often show a stronger focus on task-oriented behaviors, while women tend to emphasize emotional-oriented behaviors (Anderson & Blanchard, 1982; Parsons & Bales, 1955), which may impact their appraisals of these two types of AI usage. Specifically, men are often considered more agentic, characterized by mastery and competitiveness (Hsu et al., 2021). As men tend to maintain their dominant status, they might feel a greater sense of threat when faced with the superior task capabilities of AI (Maner et al., 2008). In contrast, women are generally perceived as more communal, exhibiting greater friendliness and expressiveness (Eisenberg & Lennon, 1983; Hsu et al., 2021; Mestre et al., 2009; Parsons & Bales, 1955). This tendency makes women more sensitive to emotional expressions and kindness from others (Qiu et al., 2022), leading them to positively evaluate AI due to the emotional support it provides. Therefore, we propose there are gender differences in the impacts of using AI. To test the proposed model, we conducted a three-phase survey involving 495 participants from various internet and high-tech companies. The theoretical model is shown in Figure 1.

Our research makes several contributions. Firstly, we shift the predominant focus from using AI for instrumental support to using AI for emotional support in the organizational research (Jia et al., 2024; Noy & Zhang, 2023; Sowa et al., 2021). We enhance the current understanding of human–AI interaction by distinguishing between two distinct yet related constructs: using AI for instrumental support and using AI for emotional support. Secondly, we complicate the relationship between human–AI interaction and job insecurity. While previous research generally suggests that human–AI interaction execrates job insecurity (Presbitero & Teng-Calleja, 2023; Yam et al., 2023), we propose a balanced view that human–AI interaction does not necessarily increase employees' insecurity, depending on the specific approaches. Finally, we integrate gender differences into the theory concerning the impacts of human–AI interaction, investigating how human–computer interaction are perceived through a gender lens. We propose that significant differences may exist between men and women in their experiences with AI for different types of human–AI interaction. This approach provides deeper insights into how gender factors shape human–AI interactions, offering valuable perspectives on the ongoing manifestation of gender differences in the context of human–computer interaction.

2. Theoretical background

AI has evolved to include a range of capabilities, from basic task processing to advanced cognitive and emotional functions (Gelbrich et al., 2021; Pauw et al., 2022; Vorobeva et al., 2022). Nowadays, people utilize AI for diverse needs, prompting corresponding responses from AI. For instance, AI is used for automation and augmentation of decision-making through automated information collection, filtering and analysis, decision suggestions, and action execution (Langer & Landers, 2021). It also provides real-time insights into employee performance and supports basic task activities such as document writing and customer information analysis (Noy & Zhang, 2023). Furthermore, distinguishing these task-related functions, the latest research indicated that AI can also develop friendships with humans, providing care and emotional comfort (Brandtzaeg et al., 2022; Gelbrich et al., 2021; Ki et al., 2020). Drawing from current researches and practical insights, we posit that individuals primarily use AI in two main scenarios: using AI for instrumental support and using AI for emotional support. We refer to using AI for instrumental support as using AI for task instruction and task assistance (Mathieu et al., 2019), whereas using AI for emotional support involves seeking empathy and reassurance from AI (Gelbrich et al., 2021).

Although both types of AI usage entail supporting individuals and fulfilling their needs, they differ significantly in several aspects, specifically in terms of content, function, implications, and applications, as delineated in Table 1. Firstly, the two types of AI support differ in content. Using

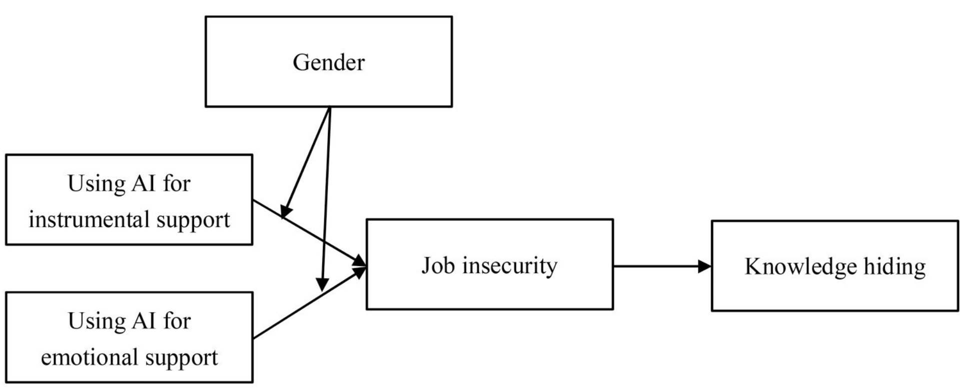

Figure 1. Conceptual model.

Table 1. Differentiated use of AI.

Characteristics	Using AI for instrumental support	Using AI for emotional support
Content	Responding to requests for task assistance involves addressing work problems, primarily through providing practical tools, gathering information, and supporting decision-making.	Responding to requests for emotional assistance involves offering reassurance and understanding, primarily through emotional communication, encouragement, and comfort.
Function	• Providing task resources. • Meeting individuals' needs for competence.	• Providing emotional resources. • Meeting individuals' needs for relatedness.
Implications for self	• Individuals may recognize their limitations and easily develop self-doubt regarding their abilities when compared to AI. • AI helps employees do their jobs better and improve the self-efficacy. • Sometimes, employees may also recognize their unique human-beings' advantages, such as creativity.	• Individuals better reflect on and understand their emotional states and needs. • AI helps employees to better recognize and deal with emotional issues and increase emotional intelligence. • Sometimes, employees may also recognize their unique human-beings' advantages, such as non-verbal communication.
Implications for AI & human-AI relation	• Perceived competence. • Overlap and replacement between human and AI task-related knowledge, skills, and abilities. • Viewing AI as a colleague or competitor. • Acknowledging its limitations.	• Perceived warmth. • Overlap and replacement between human and AI emotional-related knowledge, skills, and abilities. • Viewing AI as a friend or companion. • Acknowledging its limitations.
Implications for the workplace	• Changing organizational structures. • Altering job demands, work methods and routines. • Increasing efficiency, reducing costs, and enhancing productivity. • Risk for potential over-reliance.	• Changing social structures. • Altering emotional seeking paths and methods. • Improving mental health, reducing burnout, and increasing job satisfaction. • Risk for potential over-reliance.
Examples for application	• Automation: AI systems that automate routine tasks in industries like manufacturing, finance, and customer service. • Data analysis and decision support: AI tools that analyze large datasets to provide insights, predictions, or decision-making support. • Process optimization: AI applications that streamline workflows, optimize resource allocation, and enhance operational efficiency.	• Companions: Virtual assistants or chatbots designed to provide companionship, empathy, or psychological support. • Emotion recognition: AI that analyzes facial expressions, voice tones, or text to understand and respond to the user's emotional state. • Interactive storytelling: AI-driven narratives that adapt based on the user's emotional responses to create a more engaging experience.

AI for instrumental support involves AI responding to task demands, primarily providing information, tools, and analytical recommendations to improve work efficiency (Mathieu et al., 2019; Noy & Zhang, 2023; Radonjić et al., 2024). Conversely, using AI for emotional support involves AI responding to emotional requests, where AI expresses caring, encouragement, and sympathy (Gelbrich et al., 2021; Mathieu et al., 2019; Thoits, 2011). Secondly, for the functional aspects, using AI for instrumental support primarily provides task resources and meet the needs for competence to solve issues in the work (Jia et al., 2024; Mathieu et al., 2019; Noy & Zhang, 2023). Conversely, using AI for emotional support primarily provides emotional resources and meet the needs for relatedness, emphasizing assisting individuals in regulating feelings and emotions (Gelbrich et al., 2021; Jolly et al., 2021; Mathieu et al., 2019).

Thirdly, the two types of AI support have distinct implications for individuals, how individuals perceive AI and their relationship with AI, as well as the workplace. On the one hand, individuals gain insights about themselves through using different types of AI support. Using AI for instrumental support prompts individuals to reflect on their work abilities. Given the advanced capabilities of AI, they may recognize their work restrictions, leading to self-doubt regarding their abilities (Tang et al., 2023), although they may also sometimes recognize their unique human beings' advantages, such as creativity (Koivisto & Grassini, 2023). Notably, using AI for instrumental support help employees do their jobs better and improve the self-efficacy (Radonjić et al., 2024; Yin et al., 2024). In contrast, using AI for emotional support helps individuals reflect on and understand their emotional state and needs. Additionally, employees may recognize their unique human advantages, such as non-verbal communication (Phutela, 2015; Tang et al., 2023). Furthermore, using AI for emotional support help employees to better recognize and deal with emotional issues and increase emotional intelligence.

On the other hand, different types of AI support shape individuals' perception of AI and their relationship with it. Using AI for instrumental support highlights its effectiveness in task accomplishment. This usage makes individuals aware of its impressive competence and the overlap between AI's task-related knowledge, skills, and abilities and their own (Arias-Pérez & Vélez-Jaramillo, 2022; Tang et al., 2023). The nature of AI's assistance and its substitutive potential lead individuals to view AI either as a colleague or a competitor (Dang & Liu, 2022; Khoa et al., 2023). Additionally, individuals can also recognize AI's limitations such as its lack of creativity (Koivisto & Grassini, 2023). Regarding using AI for emotional support, individuals can perceive the warmth of AI and are more likely to regard AI as a friend or companion (Gelbrich et al., 2021; Ki et al., 2020; Song et al., 2022). Individuals may also recognize that AI's emotional capabilities overlap with, and potentially replace, human emotional knowledge, skills, and abilities to some extent through using AI for emotional support. Research indicates that AI's limited ability to empathize with others and respond to social cues is the primary reason service personnel, such as call center representatives and telemarketing employees, remain irreplaceable (Vorobeva et al., 2022). However, if AI develops the anthropomorphic capability to provide emotional support in the future, it may theoretically replace more of these service roles by reducing the perceived difference between AI and human interactions, thereby diminishing the value of human service personnel (Huang & Rust, 2023; Pelau et al., 2021). Additionally, individuals could also recognize the limitations of AI, such as its inability to engage in non-verbal communication (Phutela, 2015; Tang et al., 2023).

With respect to the implications of different types of AI support on the workplace, using AI for instrumental support can change organizational structures, alter job demands, work methods, and routines (Arias-Pérez & Vélez-Jaramillo, 2022; Jia et al., 2024; Tang et al., 2023). An illustrative example is that working in a human-AI collaborative context requires individuals to develop proficient skills in using AI (Chowdhury et al., 2022). Using AI for instrumental support increases efficiency, reduces costs, and enhances productivity, but also raises the risk of individuals becoming overly reliance on AI to meet competence needs (Tang et al., 2023). Using AI for emotional support may lead to changes in social structures, improve and change workplace relationship, and alter emotional seeking paths and methods. As Brandtzaeg et al. (2022) suggested that humans are starting to form friendships with AI chatbots, which may lead to a redefinition of the concept of friendship. Additionally, using AI for emotional support can improve mental health, reducing burnout, and increasing job satisfaction while it may also increase the risk that individuals becoming over-reliant on AI to meet relatedness needs (Kwok et al., 2015; Pauw et al., 2022).

Finally, the two types of AI support used by individuals have distinct applications. AI instrumental support most used in automation, data analysis, decision support, and work process optimization (Kanitz et al., 2023; Noy & Zhang, 2023; Radonjić et al., 2024). AI emotional support most used in providing companions, emotion recognition, and interactive storytelling (Brandtzaeg et al., 2022; Gelbrich et al., 2021; Ki et al., 2020; Song et al., 2022).

3. Hypotheses development

3.1. Using AI for instrumental support and job insecurity

Building on the distinctions between instrumental and emotional support, we further discuss the impact of these two different usages of AI on employees' job insecurity and their coping behaviors. Based on the transactional theory of stress, job insecurity can be viewed as a work stressor arising from an individual's appraisal of encounters (Debus et al., 2014; Lazarus & Folkman, 1984). Using AI for instrumental and emotional support can be viewed as different encounters with new technology, prompting employees' appraisals, which may be evaluated as irrelevant, benign-positive, or stressful (Lazarus & Folkman, 1984). Job insecurity refers to an individual's perceived powerlessness to maintain job continuity (Greenhalgh & Rosenblatt, 1984). We argue that substitutability is the key appraisal criterion generating job insecurity because AI's ability to perform tasks competently poses a potential threat to employees' job roles (Bartels et al., 2023; Lazarus & Folkman, 1984).

Using AI for instrumental support involves leveraging task resources from AI to achieve work objectives. When working with AI, employees visualize its benefits in task processing, such as its advanced information processing, extensive knowledge base, and rapid learning capabilities. This is especially true when AI can perform tasks beyond human capability. However, after experiencing the convenience AI brings, employees may reflect on themselves and develop a sense of self-doubt (Tang et al., 2023). They recognize significant the overlap between AI's task competency and their own, suggesting AI may threaten or even replace their roles in the workplace (Arias-Pérez & Vélez-Jaramillo, 2022; Tang et al., 2023). As employees increasingly rely on AI for handling tasks, they may realize that their contributions are no longer unique and irreplaceable, ultimately causing job insecurity (Arias-Pérez & Vélez-Jaramillo, 2022; Tang et al., 2023). Notably, AI applications have the tendency to alter work structures, demands, and routines (Chowdhury et al., 2022; Dwivedi et al., 2021). Employees who frequently use AI in task completion are more likely to perceive the risk of being eliminated due to an inability to adapt to these changes timely, as well as the potential loss of work status, generating a sense of powerlessness about maintaining future employment (Lee et al., 2018; Yam et al., 2023). In summary, using AI for instrumental support can be evaluated by employees as stressful, leading to increased job insecurity. Hence, we propose:

H1: Using AI for instrumental support is positively related to employees' job insecurity.

3.2. Using AI for emotional support and job insecurity

Using AI for emotional support underscores AI's emotional capabilities, which are not typically directly related to the knowledge, skills, and abilities required for task completion (Stevens & Campion, 1999). Thus, employees probably not perceive AI as overlapping with or substituting their task roles, making it more likely that they evaluate using AI for emotional support as irrelevant. Moreover, using AI for emotional support creates a safe space for individuals to express their emotions and provides additional emotional resources that help employees alleviate negative emotions. Negative emotions often arise from feelings of powerlessness, whether related to a loss of control over one's circumstances or from negative self-evaluation (Burleson, 2003). Therefore, using AI for emotional support can help employees to develop a more positive self-view and a more optimistic outlook on their situation (Burleson, 2003). This enables employees to establish a positive attitude to cope with uncertainties and challenges. Additionally, empathic response epitomizes a fundamental aspect of human nature. It communicates the sender's benevolence and friendliness, allowing recipients to interpret the sender's intention as kind (Gelbrich et al., 2021; Sevillano & Fiske, 2016). AI's empathic response can prompt employees to perceive AI as warm rather than merely a tool or machine (Gelbrich et al., 2021). This fosters a more positive view of AI and diminishes the extent of threat evaluation associated with it. Furthermore, using AI for emotional support could reduce the psychological distance between individuals and AI, leading individuals to view AI as a close and reliable friend (Gelbrich et al., 2021; Ki et al., 2020; Lv et al., 2022), thereby reducing perceived threat of AI and subsequently decrease job insecurity. In summary, using AI for emotional support provides additional emotional resources and fosters trust, encouraging individuals to perceive themselves and their relationship with AI in a more positive way. This may lead employees to regard the use of AI for emotional support as beneficial and favorable. Hence, we propose:

H2: Using AI for emotional support is negatively related to employees' job insecurity.

3.3. Job insecurity and knowledge hiding

According to the transactional theory of stress, individuals develop coping mechanisms based on their evaluation (Lazarus & Folkman, 1984). We propose that knowledge hiding constitutes a coping behavior when employees experience job insecurity, as knowledge represents the core of their competence, allowing them to maintain competitive advantages (Mudambi & Navarra, 2004; Rhee & Choi, 2017; Swift et al., 2010). Knowledge hiding refers to "an intentional attempt by an individual to withhold or conceal knowledge that has been requested by another person" (Connelly et al., 2012). Job insecurity essentially involves individuals' concerns about aligning their competency with work in the long term. In insecure circumstances, employees feel compelled to take measures to maintain or enhance their advantages. Since knowledge represents the core of competence, knowledge hiding enables employees retain proprietary information rights and attain a competitive edge relative to their human colleagues (Mudambi & Navarra, 2004; Rhee & Choi, 2017; Swift et al., 2010). When employees feel threatened, they tend to adopt knowledge hiding as a coping mechanism to preserve their knowledge advantages. Furthermore, when job insecurity arises from AI's comparative advantage and individuals cannot surpass it, maintaining an edge over human colleagues becomes crucial for future job retention. Thus, employees are more inclined to hide knowledge from colleagues to protect their competitive competences (Arias-Pérez & Vélez-Jaramillo, 2022; Serenko & Bontis, 2016). In conclusion, knowledge hiding serves as a defensive strategy triggered by job insecurity that aims to protect valuable resources, maintain competitive advantage, and regain control over environment. Thus, we propose:

H3: Job insecurity mediates the relationship between using AI for instrumental support and knowledge hiding.

H4: Job insecurity mediates the relationship between using AI for emotional support and knowledge hiding.

3.4. The moderating role of gender

We further identify a fundamental individual difference, gender, to capture how employee perceive the impact of using AI on themselves differently. Research indicated that men and women exhibit differences in the valuation and expression of instrumental and emotional behaviors (Anderson & Blanchard, 1982; Parsons & Bales, 1955). Typically, women display higher levels of communion, while men are more agentic (Hsu et al., 2021). Therefore, we predict that the gender difference would persist in the new technological contexts.

Using AI for instrumental support makes employees recognize its capabilities in task completion and its potential to supplant their task knowledge, skills, and abilities. We propose that men may perceive a greater threat from AI as a result. Due to their competitive nature and desire to showcase their superior abilities, men may experience heightened anxiety about their competences being overshadowed (Maner et al., 2008; Niederle & Vesterlund, 2007). This may lead to hostility towards AI and an amplified perception of threat of AI. Meanwhile, relying on AI to handle work tasks undermines men's perception of independence and leads to a loss of control over task processes. More importantly, as AI's involvement and importance in work increase, it suggests a growing dominance of AI, which severely threatens men's expectation for dominance (Maner et al., 2008), thus generating a strong sense of insecurity. Altogether, men are more likely to feel threatened by AI, which results in stronger job insecurity. This job insecurity caused by using AI for instrumental support prompts men to engage in coping behaviors, such as knowledge hiding. In contrast, women typically exhibit lower levels of agency, are less focused on dominance and competition (Hsu et al., 2021). Therefore, the impact of using AI for instrumental support on job insecurity is not as significant for women. Hence, we propose:

H5: Gender moderates the relationship between using AI for instrumental support and job insecurity. Specifically, the positive relationship between using AI for instrumental support and job insecurity is stronger for the men.

H6: The indirect effect of using AI for instrumental support and knowledge hiding via job insecurity is moderated by gender. Specifically, the indirect effect of using AI for instrumental support and knowledge hiding via job insecurity is stronger for the men.

Conversely, considering that women typically exhibit higher levels of communion, particularly in their sensitivity to emotional interaction (Barrett et al., 2000; Hsu et al., 2021), the impact of AI emotional support may be amplified. Research has shown that women tend to prioritize emotional behaviors and exhibit higher levels of empathy compared to men (Eisenberg & Lennon, 1983; Mestre et al., 2009). This enables women to be more sensitive to emotional support behaviors and the benevolence of others (Qiu et al., 2022). Consequently, when using AI for emotional support, women are more likely to value the understanding, reassurance, and respect expressed by AI. They are more likely to perceive and appreciate the emotional aspects of AI, leading to more favorable evaluations of AI (Cahill & Sias, 1997). Additionally, this propensity makes women more inclined to establish an emotional bond with AI (Mestre et al., 2009; Qiu et al., 2022), leading them to view AI as a friend, which further reduces the perceived threat from AI and thereby diminishes job insecurity and knowledge hiding. Unlike women, men place less emphasis on emotional aspects and are less sensitive to the benevolence of others (Cahill & Sias, 1997; Qiu et al., 2022). Consequently, emotional support does not serve as a decisive role in influencing men's appraisal of the threat posed by AI. While AI emotional support may offer some benefits, it is unlikely to substantially change men's appraisal toward AI. Therefore, the effect of using AI for emotional support on job insecurity is not significant for men. Thus, we propose:

H7: Gender moderates the relationship between using AI for emotional support and job insecurity. Specifically, the negative relationship between using AI for emotional support and job insecurity is stronger for the women.

H8: The indirect effect of using AI for emotional support and knowledge hiding via job insecurity is moderated by gender. Specifically, the indirect effect of using AI for emotional support and knowledge hiding via job insecurity is stronger for the women.

3.5. The interaction between multiple using of AI

In addition to the main hypotheses outlined above, we also propose a supplementary hypothesis regarding the interaction of different types of AI support on job insecurity and its outcome. We propose that using AI for emotional support changes individuals' attitudes towards their relationship with AI, enabling them to evaluate the benefits and threats posed by using AI for instrumental support from a more positive perspective, thus alleviating job insecurity caused by using AI for instrumental support.

Specifically, using AI for instrumental support fosters both collaborative and competitive relationships between employees and AI (Khoa et al., 2023). When employees also utilize AI for emotional support, the psychological distance between them and AI decreases, leading to their trust towards AI (Gelbrich et al., 2021; Lv et al., 2022). This encourages employees to view AI as a collaborator rather than a competitor in instrumental use. Consequently, the powerful task capabilities of AI perceived through instrumental support are more likely to be seen as an asset rather than a stressor, making employees more inclined to focus on the benefits of using AI for instrumental support rather than its potential harms. Additionally, using AI for emotional support provides extra emotional resources beyond specific tasks. This can alleviate the stress and negative emotion caused by the uncertainty and self-doubt associated with using AI for instrumental support (Burleson, 2003), thereby potentially reducing the job insecurity it induces. Conversely, when using AI for emotional support to a lesser extent, work-centered interactions alone fail to convey AI's emotional and warm aspects. The absence of an emotional connection causes employees to view AI more competitively, amplifying the perceived threat of AI replacing their skills when using AI for instrumental support, which leads to increased job insecurity.

H9: Using AI for instrumental support and using AI for emotional support interact to influence job insecurity. Specifically, the positive relationship between using AI for instrumental support and job insecurity is weaker when AI is also used for emotional support at a higher (vs. lower) level.

H10: Using AI for instrumental support and using AI for emotional support interact to influence knowledge hiding via job insecurity. Specifically, the indirect effect of using AI for instrumental support and knowledge hiding via job insecurity is weaker when AI is also used for emotional support at a higher (vs. lower) level.

4. Methodology

4.1. Sampling and data collection

We recruited participants from six internet and high-tech companies in Beijing, China for our survey sample, as these companies extensively use AI into their operations. The survey collection was completed with the assistance of these companies' HR employees. The survey was conducted online in three waves, with a two-week interval between each wave. At T1, we collected demographic variables along with measures of using AI for instrumental support and using AI for emotional support; at T2, we assessed job insecurity; and at T3, we measured knowledge hiding. We emphasized this research's implications and ensured the confidentiality in each wave survey. A total of 495 employees completed all three waves of the survey, resulting in a 76.9% completion rate. Our sample size aligns with established standards in prior AI research employing survey methods (Hu et al., 2023; Verma & Singh, 2022). Demographic statistics revealed that 311 respondents were female (62.8%), with the largest age group being 31–40 years old (65.7%). The age distribution was as follows: 25 years and below (5.1%), 26–30 years (23%), and 41–50 years (6.3%). Additionally, most participants held a bachelor's degree (57.2%), with high school education or below at 0.6%, associate degrees at 10.3%, master's degrees at 31.3%, and doctoral degrees at 0.6%.

4.2. Measurement

We employed well-established scales in this study, all of which demonstrated good reliability and validity. A Likert 5-point scale was used across all measures, all items were rated from 1 (*Strongly disagree*) to 5 (*Strongly agree*) unless other noted. Detailed measurement items are provided in Appendix A.

Using AI for instrumental support: We measured using AI for instrumental support using a 4-item scale adapted from Verma and Singh (2022). Cronbach's alpha was 0.90.

Table 2. Results of confirmative factor analyses.

Model	χ^2	df	$\Delta\chi^2$	CFI	TLI	RMSEA	SRMR
Four-factor model: using AI for instrumental support, using AI for emotional support, job insecurity, knowledge hiding	289.69	98		0.96	0.95	0.06	0.05
Three-factor model: using AI for instrumental support + using AI for emotional support, job insecurity, knowledge hiding	1099.41	101	809.72**	0.80	0.76	0.09	0.14
Two-factor model: using AI for instrumental support + using AI for emotional support, job insecurity + knowledge hiding	1395.66	103	1105.97**	0.74	0.69	0.11	0.16
One-factor model: using AI for instrumental support + using AI for emotional support + job insecurity + knowledge hiding	2345.35	104	2055.66**	0.55	0.48	0.17	0.21

Note. $N = 495$. "+" refers to combining the items to a factor. $^{**}p < 0.01$.

Using AI for emotional support: We measured using AI for emotional support with five items adapted from Methot et al. (2016). Cronbach's alpha was 0.94.

Job insecurity: Employee rated the job insecurity using a 3-item scale adapted from Verma and Singh (2022). Cronbach's alpha was 0.74.

Knowledge hiding: We measured employees' knowledge hiding with the 4-item scale developed by Rhee and Choi (2017). Items were rated from 1 (*Never*) to 5 (*Very often*). Cronbach's alpha was 0.86.

Control variables: We controlled for demographic variables, including age, education level, and organizational tenure. Research indicated that age and education level are significantly related to job insecurity: older individuals tend to report higher insecurity than younger ones, and those with lower levels of education report greater insecurity than those with higher levels of education (Cheng & Chan, 2008). Additionally, the longer employees work for their organization, the more experience and ability they will have, and the knowledge they have developed in their jobs is what makes them less likely to feel replaced and threatened by AI (Ng & Feldman, 2010; Shoss, 2017). Notably, whether it is controlled or not, it does not affect the significant result.

5. Results

5.1. Analytical strategy

Path analysis was conducted in Mplus 8.3 to test the hypotheses, simultaneously estimating all parameters (Muthén & Muthén, 2017). Prior to analysis, all predictors were centered, and the interaction terms were generated by multiplying the centered values of independent variables and moderators (Hofmann & Gavin, 1998). Simple slope analysis, as recommended by Aiken et al. (1991), was utilized to demonstrate specific moderating effects. For the proposed conditional indirect effects, 5,000 bootstrapping iterations were performed to calculate 95% confidence intervals (Edwards & Lambert, 2007; Preacher & Hayes, 2008). Additionally, significant differences in indirect effects were examined.

5.2. Non-response bias test

Using the method outlined by Talukder et al. (2025) and following Armstrong and Overton (1977) approach, we divided the sample into two independent groups based on the median completion time for each stage. Independent sample t-tests were conducted to evaluate whether significant differences existed in responses to key variables, thereby assessing potential non-response bias. The results revealed no statistically significant differences, indicating that non-response bias was negligible and affirming the validity of the research findings.

5.3. Common method bias test

We conducted Harman's single-factor test to evaluate the extent of common method bias in this study. The analysis showed that the first factor accounted for 34.9% of the variance, which is below the critical threshold of 50% (Podsakoff et al., 2003). Therefore, common method bias is unlikely to significantly affect the results of this study.

5.4. Confirmative factor analyses

Prior to hypothesis testing, confirmatory factor analysis (CFA) was conducted to assess measurement fit. As presented in Table 2, the results revealed that the full measurement model with four factors (Using AI for instrumental support, Using AI for emotional support, job insecurity, and knowledge hiding) fit to the data well ($\chi^2(df)$ = 289.69(98), CFI = 0.96, TLI = 0.95, RMSEA = 0.06, SRMR = 0.05) compared to alternative models. When combining all focal variables into one factor, the model fit was significantly worse ($\chi^2(df)$ = 2345.35(104), CFI = 0.55, TLI = 0.48, RMSEA = 0.17, SRMR = 0.21; $\Delta\chi^2(\Delta df)$ = 2055.66(6), $p < 0.01$). Therefore, the results provided support for the distinctiveness of the four measured variables.

5.5. Hypothesis testing

Descriptive statistics and correlations are presented in Table 3, while path analysis results are summarized in Table 4. Hypotheses 1 and 2 proposed that using AI for instrumental support is positively related to job insecurity, and using AI for emotional support is negatively related to job insecurity. The results showed a significant positive relationship between using AI for instrumental support and job insecurity ($b = 0.10$, $SE = 0.05$, $p < 0.05$ in Table 4) and a significantly negative relationship between using AI for emotional support and job insecurity ($b = -0.09$, $SE = 0.04$, $p < 0.05$). Thus, Hypothesis 1 and 2 were supported.

Hypothesis 3 and 4 posited the mediation effect. In the mediation model, job insecurity was found to be positively

Table 3. Descriptive statistics and correlations.

	Mean	*SD*	1	2	3	4	5	6	7	8
1. Gender	0.37	0.48								
2. Age	2.73	0.65	0.00							
3. Education	3.21	0.65	−0.16**	0.15**						
4. Organizational tenure	1.91	0.93	−0.05	0.40**	0.12**					
5. Using AI for instrumental support	2.88	0.89	0.06	−0.04	−0.21**	−0.02	(0.90)			
6. Using AI for emotional support	2.58	0.98	−0.05	−0.02	−0.21**	0.06	0.54**	(0.94)		
7. Job insecurity	3.09	0.79	0.04	0.07	0.17**	−0.09	0.01	−0.10*	(0.74)	
8. Knowledge hiding	2.26	0.73	0.05	−0.04	0.20**	−0.07	−0.10*	−0.01	0.24**	(0.86)

Note. $N = 495$. Gender: 0 = female, 1 = male. Age: 1 = 25 years old or younger, 2 = 26–30 years old, 3 = 31–40 years old, 4 = 41–50 years old, 5 = 50 years old or older. Education: 1 = High school or below, 2 = Associate's degree, 3 = Bachelor's degree, 4 = Master's degree, 5 = Doctorate (PhD). Organizational tenure: 1 = Less than 3 years, 2 = 3–5 years, 3 = 6–10 years, 4 = 10 years or more. Cronbach's αs are reported along the diagonal. *$p < 0.05$. **$p < 0.01$., two-tailed.

Table 4. Results of path analysis.

	Mediation model				Moderated mediation model				Supplementary analysis			
	Job insecurity		Knowledge hiding		Job insecurity		Knowledge hiding		Job insecurity		Knowledge hiding	
	b	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Intercept	3.09**	0.04	1.64**	0.13	3.10**	0.03	1.65**	0.13	3.13**	0.04	1.66**	0.13
Gender	0.07	0.07	0.13*	0.07	0.08	0.07	0.13*	0.07	0.08	0.07	0.13*	0.07
Age	0.12*	0.06	−0.07	0.05	0.12*	0.06	−0.07	0.05	0.12*	0.06	−0.07	0.05
Education	0.22**	0.06	0.22**	0.05	0.23**	0.06	0.22**	0.05	0.21**	0.06	0.22**	0.05
Organizational tenure	−0.12**	0.04	−0.04	0.04	−0.11**	0.04	−0.04	0.04	−0.12**	0.04	−0.04	0.04
Using AI for instrumental support	0.10*	0.05	−0.12**	0.04	0.10*	0.05	−0.11**	0.04	0.11*	0.05	−0.11**	0.04
Using AI for emotional support	−0.09*	0.04	0.11**	0.04	−0.09*	0.04	0.10**	0.04	−0.07	0.04	0.11**	0.04
Using AI for instrumental support × gender					0.01	0.09	−0.05	0.09	−0.03	0.10	−0.07	0.09
Using AI for emotional support × gender					0.22*	0.09	0.06	0.08	0.25**	0.09	0.07	0.08
Using AI for instrumental support × using AI for emotional support									−0.09*	0.04	−0.03	0.03
Job insecurity			0.20**	0.04			0.20**	0.04			0.19**	0.04
R^2	0.06**	0.02	0.12**	0.03	0.08**	0.02	0.12**	0.03	0.07**	0.02	0.12**	0.03

Note. $N = 495$. *$p < 0.05$. **$p < 0.01$., two-tailed.

related to knowledge hiding ($b = 0.20$, $SE = 0.04$, $p < 0.01$). The bootstrapping results indicated significant indirect effects of using AI for instrumental support on knowledge hiding via job insecurity (*estimate* = 0.020, $SE = 0.011$, 95% CI [0.004, 0.040]) and using AI for emotional support on knowledge hiding via job insecurity (*estimate* = −0.018, $SE = 0.011$, 95% CI [−0.038, −0.003]), supporting the Hypothesis 3 and 4.

Hypothesis 5 proposed a gender difference between using AI for instrumental support and job insecurity, suggesting that men using AI for instrumental purposes would feel more job insecurity. Hypothesis 6 proposed a moderated mediation effect. However, in the moderated mediation model (Table 4), the interaction term of using AI for instrumental support and gender was not significantly associated with job insecurity ($b = 0.01$, $SE = 0.09$, $p = 0.96$). Thereby, Hypothesis 5 and 6 was not supported.

Hypothesis 7 posited a gender difference between using AI for emotional support and job insecurity, suggesting that women using AI for emotional support would feel less job insecurity. Hypothesis 8 proposed a moderated mediation effect. The moderated mediation model revealed that the interaction term of using AI for emotional support and gender was significantly positive associated with job insecurity ($b = 0.22$, $SE = 0.09$, $p < 0.05$). As depicted in Figure 2, simple slope tests for different genders showed a significant negative correlation between using AI for emotional support and job insecurity for women ($b = -0.20$, $SE = 0.06$, $p < 0.05$), while it was not significant for men ($b = 0.01$, $SE = 0.06$, $p = 0.83$), with a significant difference

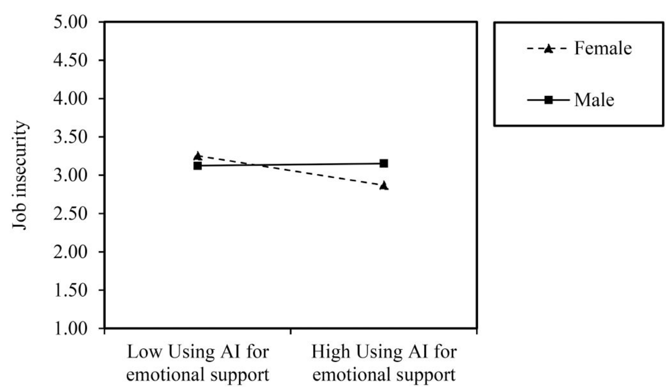

Figure 2. Gender difference between using AI for emotional support and job insecurity.

(*difference* = 0.21, $SE = 0.08$, $p < 0.05$). For Hypothesis 8, the bootstrapping results indicated a significant indirect effect of using AI for emotional support on knowledge hiding via job insecurity for women (*estimate* = −0.039, $SE = 0.016$, 95% CI [−0.070, −0.017]), while it was not significant for men (*estimate* = 0.002, $SE = 0.014$, 95% CI [−0.019, 0.026]). The difference between these indirect effects was significant (*difference* = 0.041, $SE = 0.021$, 95% CI [0.013, 0.083]). Therefore, Hypothesis 7 and 8 were supported.

5.6. Supplementary analysis

In addition to our primary hypotheses, we explored whether interactions between different uses of AI could impact employee job insecurity through supplementary analyses. As

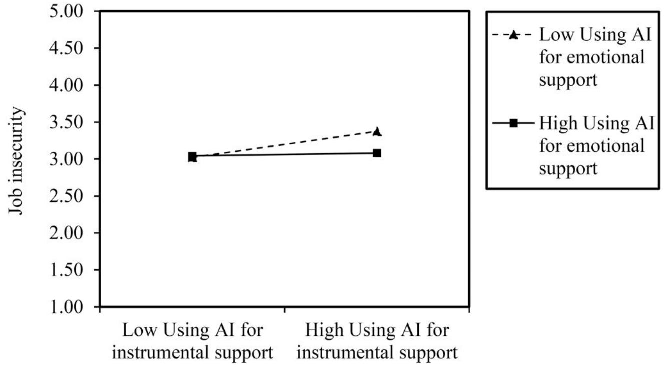

Figure 3. Interactive effect of using AI for instrumental support and using AI for emotional support on job insecurity.

presented in Table 4, the interactive effect of using AI for instrumental support and using AI for emotional support on job insecurity was significant ($b = -0.09$, $SE = 0.04$, $p < 0.05$). As depicted in Figure 3, the simple slopes test at ±1 standard deviation revealed that the correlation between using AI for instrumental support and job insecurity was significant and positive when using AI for emotional support is low ($b = 0.20$, $SE = 0.06$, $p < 0.01$) but was not significant when using AI for emotional support is high ($b = 0.03$, $SE = 0.06$, $p = 0.60$). The difference between the two slopes was also significant (*difference* $= -0.17$, $SE = 0.07$, $p < 0.05$), thus supporting H9.

Furthermore, we found using AI for emotional support moderated the indirect effect of using AI for instrumental support on knowledge hiding via job insecurity. The bootstrapping results indicated a significant indirect effect of using AI for instrumental support on knowledge hiding via job insecurity when using AI for emotional support is low (*estimate* $= 0.038$, $SE = 0.021$, 95% CI [0.016, 0.070]), but it was not significant when using AI for emotional support is high (*estimate* $= 0.006$, $SE = 0.014$, 95% CI [−0.016, 0.030]). The difference between these indirect effects was also significant (*difference* $= -0.033$, $SE = 0.020$, 95% CI [−0.073, −0.005]). Therefore, the findings suggest that when employees actively utilize AI for emotional support, they experience a notable decrease in job insecurity stemming from their using AI for instrumental support. The reduction in job insecurity further leads to a decrease in knowledge hiding behaviors among employees, thus supporting H10.

6. Discussion and conclusions

6.1. Discussion

Although the majority of studies suggest that AI usage leads to job insecurity, they primarily focus on the context of AI usage for tasks, thereby confounding the relationship between AI usage and job insecurity. Drawing on the transactional theory of stress, we investigated the differentiated effects of two types of AI usage—using AI for instrumental support and using AI for emotional support—on job insecurity and knowledge hiding. Our findings suggest that the impact of human–AI interaction on individuals' psychological processes and work behavior depends not only on whether AI is used, but also on how it is used, as well as the influence of individual gender roles on the interpretation of AI interactions.

Our findings reveal that using AI for instrumental support significantly increases employees' job insecurity ($b = 0.10$, $SE = 0.05$, $p < 0.05$), aligning with prior research. This underscores that AI-induced job insecurity predominantly stems from perceived replacement threats due to the overlap between AI's and employees' capabilities. These results validate and extend the applicability of earlier research. However, in contrast to previous studies, we distinguish between different types of AI usage, demonstrating that using AI for emotional support reduces job insecurity ($b = -0.09$, $SE = 0.04$, $p < 0.05$). This finding offers a novel perspective, demonstrating the positive impact of using AI for emotional support in alleviating job insecurity. Additionally, it highlights the potential benefits of developing AI's emotional functionalities for improving individual positive work psychological processes and behaviors. These results confirm our hypothesis that the impact of AI usage on employees depends on the specific type of usage.

Furthermore, the gender difference effects indicate that individuals of different genders may have varying perspectives and experiences in human–AI interactions. Specifically, women experience a more pronounced reduction in job insecurity when using AI for emotional support compared to men ($b = 0.22$, $SE = 0.09$, $p < 0.05$). This finding aligns with our hypothesis, as differences in levels of communion between men and women (Hsu et al., 2021) may lead women to experience more benevolence and emotional value provided by AI, leading to more favorable evaluations of AI and perceived less threat (Maner et al., 2008; Niederle & Vesterlund, 2007), which in turn, diminishes job insecurity.

However, no gender differences are observed in the impact of AI instrumental support ($b = 0.01$, $SE = 0.09$, $p = 0.96$), which contradicts our hypothesis. Several factors may explain why women also feel insecure when using AI for instrumental support. Firstly, men traditionally hold dominant positions in the workplace (Brescoll, 2016; Glass & Cook, 2016). When AI threatens the opportunities for men, it may transmit pressures and further limit the development for women, who are already at a disadvantage (Wynn & Correll, 2018). Secondly, gender stereotypes also persist in the context of AI technology, portraying women as less proficient in high-tech fields compared to men (Leslie et al., 2015; Young et al., 2023). These stereotypes deepen biases against women, leading to increased challenges and unfair treatment in the workplace, thereby exacerbating their concerns about future prospects. Additionally, it may also cause undermine women's confidence in using technology to support their work, believing they may believe they lack the necessary technical skills (Cech et al., 2011; Young et al., 2023). Therefore, these factors contribute to minimizing the differences between men and women, resulting in women experiencing equally strong job insecurity when using AI for instrumental support.

6.2. Theoretical contribution

Our research makes several theoretical contributions. Firstly, it shifts the focal focus of existing literature on human–AI interaction in the workplace. Current studies predominantly explore how usage of AI task functions affect employees' outcomes (Bankins et al., 2024; Verma & Singh, 2022), overlooking interactions beyond task-related aspects, particularly in the emotional domain. AI can increasingly recognize human emotions through text, voice, and facial expression analysis, and respond emotionally (Saxena et al., 2020). Chatbots and virtual agents with these emotional capabilities are widely used to support mental health and provide virtual companionship (Pauw et al., 2022; Strohmann et al., 2023). We believe using AI for emotional support is likely to have significant potential impacts on employees' psychological states and behaviors. On the one hand, emotional support provides emotional resources that influence their emotion regulation, thereby significantly impacting the workplace outcomes (e.g., well-being and satisfaction, performance, interpersonal relationships) (Ashkanasy & Dorris, 2017; Du et al., 2018). On the other hand, using AI for emotional support may reshape the human-AI or human-human relationship. Research have indicated that emotional support from AI can enhance individuals' willingness to use and trust AI (Gelbrich et al., 2021; Lv et al., 2022), thereby promoting collaboration between humans and AI, as well as reshaping the workplace relationships. Therefore, it is essential to examine the impacts of using AI for emotional support in the workplace. By delineating the two primary types of support derived from AI, we shed light on a novel perspective for exploring the complex impacts of human–AI interaction and advance the theory of human–AI interaction in the workplace.

Secondly, we complicate the relationship between human–AI interaction and job insecurity. Although most studies suggest that prevalence of AI induces job insecurity, we argue that confounding effects may be present due to the lack of differentiation between the approaches to using AI (Arias-Pérez & Vélez-Jaramillo, 2022; Presbitero & Teng-Calleja, 2023; Yam et al., 2023). By distinguishing between two AI use cases, instrumental and emotional, we aim to unravel these underexplored findings. Our results indicate that in instrumental approaches, AI and human have a competency overlap in completing their work, making it perceived as a threat. However, the emotional functionalities of AI do not typically substitute for employees' knowledge, skills and abilities in their job; instead, they provide emotional resources that help employees to cope with stress and insecurity. Our research confirms the differential impact of using AI for instrumental support versus emotional support on job insecurity. Furthermore, we reveal the interactions between multiple types of AI usage, noting that emotional support from AI mitigates the job insecurity caused by using AI for instrumental support. This further supports the idea that exploring the relationship between AI and job insecurity should fully consider the specific types of AI tools being used by employees. Through this distinction, we reconcile the inconsistent views in existing research regarding whether AI triggers employees' perceptions of being replaced, which inspires us to adopt a more nuanced view of the prevalence of AI in the workplace.

Thirdly, while the gendered effects of human–AI interaction remain underexplored in existing research (Ahn et al., 2022; Ofosu-Ampong, 2023), our study reveals significant differences in how men and women response when using AI. These findings provide important theoretical insights into the role gender plays in shaping the impacts of human–AI interactions. Our study demonstrates the gender difference in the context of AI by examining the interactions between user gender and AI instrumental and emotional support. Previous research has explored whether AI features are masculinized or feminized, suggesting that AI with female characteristics is perceived as warmer, while AI with male characteristics is considered more capable (Ahn et al., 2022). This topic is inherently related to our research. While instrumental support and emotional support are not explicitly gendered, the task-oriented nature of interactions and the emotion-oriented nature of interactions partially align with traditional male and female role stereotypes to some extent, enabling individuals to perceive distinctions. Our results highlight the varying perceptions of these gendered behaviors among different gender groups, noting that AI exhibiting feminine behaviors is more likely to be accepted by women. It reveals the inherent resonance between AI functions and gender characteristics, providing new evidence for the influence of gender factors in human–AI interactions. Future research could build on our work to further explore the impact of male and female users' engagement with different types of AI tools on their task accomplishment or relationship maintenance in daily work.

6.3. Practical implication

First, our findings carry implications for the design and development of AI. We uncover the varying impact of different AI functions and highlight the positive influence of emotional AI usage on shaping the human-AI relationship. Therefore, prioritizing the integration of emotional expression capabilities in AI development is crucial. Designing a more humanized technical support system that enables AI to comprehend and respond to users' emotional needs and provide emotional support can effectively mitigate potential negative impacts associated with the introduction of new technologies. This approach enhances user acceptance and trust in AI systems, thereby reducing resistance to AI application.

Secondly, our study offers theoretical guidance for organizations seeking to mitigate the negative impacts of AI applications. Organizations can proactively promote and underscore the emotional utility of AI to mitigate the rise in employees' job insecurity resulting from the using AI for instrumental support, as well as the increase in knowledge hiding. For instance, organizations can orient employees towards a comprehensive understanding and utilization of AI tools, fostering their knowledge and acceptance of AI as an emotional support tool. They can also provide guidance on effectively employing AI to manage emotional stress and distress through enhanced training in emotional AI use. Additionally, enterprises can clarify the role of AI as an auxiliary tool to alleviate employees' apprehensions about AI replacing them, emphasizing its collaborative nature in task completion. Simultaneously, organizations can offer relevant skill training to foster the development of employees' unique skill advantages, thereby enhancing their confidence in utilizing AI.

Third, elucidating the disparities in men's and women's responses to using different types of AI support can enable individuals to recognize how their gender roles influence their job insecurity stemming from AI use. This awareness enables individuals to adopt a more rational and objective perspective towards AI and find more suitable ways to utilize this tool. Furthermore, these findings suggest that AI should be customized to meet individual needs. For instance, AI systems should be personalized to allow men and women to choose their preferred communication modes with AI according to their preferences.

6.4. Limitations and prospects

Our research also has some limitations. Firstly, while we distinguish the task-related and emotional-related use of AI and examine their impacts, further exploration of the differentiated effects of these two types of AI usage is necessary. For example, Tang et al. (2023) proposed that the frequency of interaction with AI enhances individuals' need for affiliation and loneliness. This finding applies to situations where individuals use AI for instrumental support. However, when focusing on the context of using AI for emotional support, the emotional resources and companionship provided by AI are likely to reduce feelings of loneliness. Additionally, using AI for emotional support can help individuals manage their emotions positively, thereby enhancing their existing relationships and overall social network. Future research could further investigate the influence of different AI usages on interpersonal relationships and social networks in the workplace. Moreover, refining human–AI interaction into instrumental and emotional support underscores the importance of the type of AI usage. However, exploring the specific content of these two types of support is equally significant. When individuals seek emotional support from AI, the nature of the issues discussed—whether related to workplace concerns or personal matters like family problems—could influence the outcomes. While workplace-related emotional support might directly impact workplace behavior, non-work-related emotional support can still provide valuable emotional resources. Exploring the differences in the effects of these specific support contents is necessary. Similarly, when individuals use AI for instrumental support, the nature of the interaction—whether AI directly generates solutions and makes decisions, or provides knowledge and analysis for the individuals to make decisions—might lead to different perceptions of AI and self (e.g., AI awareness, self-efficacy, work meaningfulness). This could result in varied subsequent behaviors (e.g., work involvement) and warrants further investigation.

Secondly, although we discuss the relationship between AI use and job insecurity by distinguishing different types of AI support, we believe it is essential to consider the substitution effects of AI more cautiously. We propose that the extent to which AI's instrumental and emotional capacities substitute for individual job skills varies, which is critical in determining whether individuals perceive AI as a threat. We argue that in many work contexts, using AI for instrumental support may overlap with human competencies, while using AI for emotional support may not. However, emotional functionalities from AI can also sometimes substitute for employee knowledge, skills, and abilities, particularly in roles where emotional labor is primary, such as in the hospitality and tourism industries. In such cases, AI's emotional capabilities may indeed pose a threat. Many studies have indicated that emotionally capable robots are more trusted and accepted by consumers in the service industry (Lv et al., 2022; Pelau et al., 2021). This reduces the difference between AI and human-provided emotional services, potentially making service employees feel insecure. It is worth noting that our sample did not include these industries and future research could investigate this group further to deepen our understanding of the effects of using AI for emotional support.

Finally, we used a survey with self-reported data from employees. Although the survey was conducted in three waves, establishing causality was not feasible. Future research could employ experimental methods to further validate the causality of the theoretical model proposed in this research. Furthermore, this study did not fully address common method biases, despite the use of multiwave measures and more favorable results for discriminant validity. Future research could mitigate the issues by collecting data from multiple sources, including objective measures to capture patterns of AI usage. While subjective assessments of individual AI usage have been considered reasonable in prior studies, future research could enhance findings by employing objective metrics, such as data on the duration and frequency of interactions with AI, automatically captured by digital platforms.

6.5. Conclusion

We unveil the distinct effects of using AI for instrumental and emotional support, enriching our comprehension of the multifaceted impact of AI usage. Furthermore, we investigate gender difference in the impacts of AI to gain further insight into the role of gender in the emerging technologies. This research contributes to a more profound understanding of the diverse interactions between humans and AI, sparking further exploration and contemplation regarding the ramifications of AI utilization.

Disclosure statement

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ORCID

Jiaying Chen http://orcid.org/0009-0001-7690-3041
Jiaxin Xue http://orcid.org/0000-0001-5478-1285
Yuhui Li http://orcid.org/0000-0002-3171-2380

Data availability statement

Data will be made available on request.

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About the authors

Jiaying Chen is a PhD student in the School of Labor and Human Resources at Renmin University of China. Her research interests include digital transformation, human–AI interaction, leadership.

Jiaxin Xue is a PhD student in the School of Labor and Human Resources at Renmin University of China. His research interests include leadership, time management, new trends in the workplace.

Yuhui Li is a Professor at the School of Labor and Human Resources at Renmin University of China. Her research interests focused on leader-member exchange, temporal leadership and AI-enabled human resource management. Her work has been published in Academy Management Journal, Journal of Applied Psychology, and Personnel Psychology.

Wenhao Luo is a professor at the School of Economics and Management at North China University of Technology. His research focuses on human resource management and leadership behaviors.

Appendix A. Measurement items.

Construct		Items	Source
Using AI for instrumental support	1.	I use AI to help make decisions in real-time.	Verma and Singh (2022)
	2.	I use AI to make decisions about what methods I should use to complete my work.	
	3.	I use AI to perform a variety of tasks in a short time.	
	4.	I use AI to get direct and clear information about the effectiveness (i.e., quality and quantity) of my job performance.	
Using AI for emotional support	1.	I use AI to boost my spirits when I feel low.	Methot et al. (2016)
	2.	I use AI to gain related personal experiences as an alternative perspective to my problems.	
	3.	I use AI to get encouragement and emotional support.	
	4.	I use AI to listen to me when I'm frustrated about something and need to vent.	
	5.	AI empathize with my concerns and feelings.	
Job insecurity	1.	I think that AI will replace me in the future.	Verma and Singh (2022)
	2.	I think using AI for a long time will make me dependent on them.	
	3.	I think the rise and development of AI will likely lead to unemployment.	
Knowledge hiding	1.	I agreed to help him/her but never really intended to.	Rhee and Choi (2017)
	2.	I pretended that I did not know the information.	
	3.	I said that I did not know even though I did.	
	4.	I tried to hide innovative solutions and achievement.	