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The mental health implications of artificial intelligence adoption: the crucial role of self-efficacy

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The rapid adoption of artificial intelligence (AI) in organizations has transformed the nature of work, presenting both opportunities and challenges for employees. This study utilizes several theories to investigate the relationships between AI adoption, job stress, burnout, and self-efficacy in AI learning. A three-wave time-lagged research design was used to collect data from 416 professionals in South Korea. Structural equation modeling was used to test the proposed mediation and moderation hypotheses. The results reveal that AI adoption does not directly influence employee burnout but exerts its impact through the mediating role of job stress. The results also show that AI adoption significantly increases job stress, thus increasing burnout. Furthermore, self-efficacy in AI learning was found to moderate the relationship between AI adoption and job stress, with higher self-efficacy weakening the positive relationship. These findings highlight the importance of considering the mediating and moderating mechanisms that shape employee experiences in the context of AI adoption. The results also suggest that organizations should proactively address the potential negative impact of AI adoption on employee well-being by implementing strategies to manage job stress and foster self-efficacy in AI learning. This study underscores the need for a human-centric approach to AI adoption that prioritizes employee well-being alongside technological advancement. Future research should explore additional factors that may influence the relationships between AI adoption, job stress, burnout, and self-efficacy across diverse contexts to inform the development of evidence-based strategies for supporting employees in AI-driven workplaces.

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Introduction

The advent of artificial intelligence (AI) has changed how modern businesses operate, compete, and create value (Budhwar et al. 2022; Davenport and Ronanki, 2018). Rapid advancements in AI have allowed businesses to streamline complex processes, automate formerly manual ones, make better decisions, and use more resources (Berente et al. 2021; Brynjolfsson and McAfee, 2017; Chen et al. 2023; Makridis and Mishra, 2022; Uren and Edwards, 2023). The success of AI adoption depends on human factors, including the health and adaptability of workers who are expected to interact with AI systems (Brock and von Wangenheim, 2019; Makridis and Han, 2021; Wu et al. 2022). This matter is becoming increasingly important as AI is constantly being incorporated into more organizational functions.

AI adoption in an organization is related to the integration and deployment of AI technologies across various functions, processes, and decision-making activities (Dwivedi et al. 2019). Organizations are increasingly adopting AI-based systems, tools, and algorithms to improve their productivity, efficiency, creativity, and competitive advantages (Berente et al. 2021; Davenport and Ronanki, 2018; Makridis and Mishra, 2022; Uren and Edwards, 2023). Because workers are integral in ensuring that AI works as intended and its full potential is reached, it is necessary to fully comprehend how AI will affect them before implementing it in the workplace (Berente et al. 2021; Brynjolfsson and McAfee, 2017; Chen et al. 2023; Makridis and Mishra, 2022; Uren and Edwards, 2023; Rai, Constantinides and Sarker, 2019).

The implementation of AI within organizations has significant repercussions for employees, affecting their perceptions, attitudes, behaviors, and overall well-being (Bankins et al. 2024; Budhwar et al. 2022; Pereira et al. 2023). Therefore, research is needed to examine how workers adapt to and manage the disruptive changes brought about by AI (Glikson and Woolley, 2020) because these technologies are changing the nature of work and workers' roles.

Particular attention should be given to burnout as it pertains to employee well-being in the context of AI deployment. The symptoms of burnout—emotional tiredness, depersonalization, and a diminished feeling of personal achievement—and its devastating effects on workers and organizations alike are seen very commonly in the modern workplace (Maslach et al. 2001). The introduction of AI in the workplace can intensify burnout by imposing new job demands, altering job characteristics, and disrupting established work routines (Dwivedi et al. 2021). Employees may experience increased stress and burnout due to worries about job security, spurred by concerns that they could be replaced by AI (Brougham and Haar, 2018; Wu et al. 2022).

Given the significant effects of burnout on employee well-being, organizational productivity, and talent retention (Bakker and Demerouti, 2017), it is crucial to investigate the antecedents and mechanisms of burnout in the context of AI adoption. Such investigations would enable organizations to develop targeted interventions and support systems that enhance employee resilience and well-being in AI-driven work environments (Berente et al. 2021; Chen et al. 2023; Makridis and Mishra, 2022; Uren and Edwards, 2023).

Although academics agree on the importance of studying how AI affects workers, the current literature contains many gaps. First, few studies have examined how AI adoption affects employees' mental health (particularly burnout) in the workplace (Bankins et al. 2024; Budhwar et al. 2022; Pereira et al. 2023; Makarius et al. 2020). Moreover, few empirical studies have explored how AI adoption affects the mental health of employees, even though many have examined the practical aspects of AI deployment and the possible advantages it could give

organizations (Bankins et al. 2024; Pereira et al. 2023). Important insights into the unforeseen effects of AI adoption on mental health and organizational strategies to reduce burnout in AI-driven workplaces can be gained from studying the correlation between the two (Berente et al. 2021; Uren and Edwards, 2023). If employee well-being is to be safeguarded and long-term organizational success is to be ensured in the age of AI, this knowledge gap must be filled in light of the growing number of mental health problems in contemporary workplaces and the possibility that AI will disturb established work patterns and job responsibilities (Chen et al. 2023; Makridis and Mishra, 2022).

Second, inadequate attention has been given to the mediators and moderators of the link between AI adoption and employee burnout (Bankins et al. 2024; Budhwar et al. 2022; Pereira et al. 2023). Prior research has mostly focused on the direct effects of AI adoption on different organizational outcomes while ignoring the complex psychological processes and boundary conditions that affect the relationship between AI adoption and burnout. Obtaining a complete understanding of the AI adoption-burnout nexus requires an investigation into the mediating variables that explain how AI adoption increases job stress and burnout (Budhwar et al. 2022; Meyer and Hünefeld, 2018). A key mediator in the association between AI adoption and burnout is job stress, given that AI can increase job expectations, make role ambiguity more apparent, and create a feeling of job insecurity (Wu et al. 2022). By examining the function of work stress as a mediator, this research seeks to shed light on the mental health consequences of AI adoption.

The third gap in research is closely related to the second one—namely, researchers have not explored how factors related to self-efficacy, such as confidence in one's capability to learn AI, could weaken the harmful impacts of AI adoption on mental health in the workplace (Bankins et al. 2024). A person's self-efficacy (i.e., their confidence in their abilities to do a job well or deal with a challenging situation; Bandura, 1986), can help workers cope with workplace stresses (Bakker and Demerouti, 2017). An individual's self-efficacy in AI learning, defined as their confidence in their capacity to gain and use AI-related information and skills, is a potential protective factor in the realm of AI adoption that can help mitigate the negative effects of AI-induced stress on the mental health of employees (Nisafani et al. 2020). Compared to other workers, those who believe in their abilities to learn AI may be better able to adjust to changing job demands, take advantage of AI's opportunities, and feel in charge and competent, even as their work is transformed by AI (Berente et al. 2021; Chen et al. 2023; Uren and Edwards, 2023).

Further empirical research is needed to explore the relationship between AI and burnout, as few studies have examined the role of self-efficacy in AI learning, despite its theoretical and practical importance (De Vos et al. 2021). It is critical to fill this knowledge gap in order to learn how AI adoption affects workers' mental health, what factors limit this effect, and how workers' resilience and well-being can be improved in AI-driven workplaces.

Using the job demands-resources (JD-R) model and social cognitive theory (SCT) as supplementary theoretical frameworks, this study seeks to fill these research gaps. The JD-R model provides a comprehensive framework for comprehending how job demands, like those linked to AI adoption, can cause stress in the workplace and, eventually, burnout. It also highlights how job resources can protect against the detrimental impacts of job demands on employee health and happiness (Demerouti et al. 2001). The JD-R model can be used to examine the role of job stress as a mediator between AI adoption and burnout by offering a theoretical framework that views AI adoption as an occupational requirement that forces workers to learn new skills, adapt

to changing technology, and deal with growing complexity and uncertainty (Bankins et al. 2024; Budhwar et al. 2022).

Consistent with the JD-R model, SCT argues that people's beliefs in their abilities determine how they react to stressful situations, the problems they encounter, and the actions they take to overcome them (Bandura, 1986). This research uses SCT to investigate how self-efficacy in AI learning mitigates the detrimental impacts of AI adoption on stress at work. Combining the JD-R model with SCT shows how AI adoption, job stress, self-efficacy in AI learning, and burnout interact with each other. According to previous research in organizational psychology and human-AI interaction, this is done by integrating the strengths of both theories (Bankins et al. 2024; Budhwar et al. 2022; Pereira et al. 2023).

This study aims to answer the following research questions:

1. How does AI adoption in organizations influence employee burnout?
2. What is the role of job stress in mediating the relationship between AI adoption and employee burnout?
3. To what extent does self-efficacy in AI learning moderate the relationship between AI adoption and job stress?

By addressing these questions, we seek to provide a comprehensive understanding of the complex interplay between AI adoption, job stress, burnout, and self-efficacy as they relate to AI learning in modern organizations.

We believe that the literature on AI adoption and employee mental health is significantly enhanced by this study for several reasons. First, it fills a knowledge gap by investigating the connection between AI adoption and burnout among workers. Second, it examines how stress in the workplace mediates the connection between AI adoption and burnout, illuminating the mental pathways by which AI adoption impacts workers' mental health. Third, it explores how self-efficacy in AI learning may weaken the detrimental impacts of AI adoption on job stress and burnout at work by highlighting the importance of personal traits in workers' reactions to AI-related work demands. Finally, this study advances theory and practice in AI and organizational psychology by integrating the JD-R model and SCT. It also presents a comprehensive theoretical framework for understanding the complex dynamics of AI adoption, job stress, and employee burnout.

Theory and hypotheses

AI adoption and burnout. We propose that AI adoption in an organization will increase employee burnout. Adopting AI is a complicated and multi-stage process that begins with raising awareness and conducting exploratory research and continues through large-scale implementation and ongoing refinements (Kaplan and Haenlein, 2020). A comprehensive assessment of an organization's preparedness is required, which involves looking at, for example, data availability, human capital, leadership support, technical infrastructure, and the culture of the company (Berente et al. 2021; Chen et al. 2023; Magistretti et al. 2019; Makridis and Mishra, 2022; Uren and Edwards, 2023). The proper prioritization of AI use cases is required for organizations to achieve their strategic goals (Davenport and Ronanki, 2018). In addition, the ethical, social, and governance concerns raised by AI technologies must be addressed in order to facilitate their responsible and transparent deployment (Chen et al. 2023; Dwivedi et al. 2019). In order to fully utilize AI and keep employees engaged and well-cared-for, organizations must adjust their strategies, provide reskilling and upskilling opportunities, and cultivate a culture of lifelong learning (Magistretti et al. 2019; Makridis and Mishra, 2022; Uren and Edwards, 2023).

Prolonged interpersonal stresses in one's job can lead to burnout, a mental condition defined by emotional weariness, depersonalization, and a diminished sense of personal success (Maslach and Leiter, 2016; Maslach et al. 2001). Depersonalization is characterized by a negative, detached, and unempathetic attitude toward one's work and colleagues, while emotional exhaustion involves feelings of being emotionally drained and overextended (Maslach et al. 2001; Shirom and Melamed, 2006). Reduced self-confidence causes unfavorable assessments of one's abilities and, ultimately, discontent with one's life (Maslach et al. 2001; Leiter and Maslach, 2016). Burnout sets in when a person's emotional and physical resources are exhausted because their work environment is unsuitable (Leiter and Maslach, 2003). Research has shown that it can harm both individuals' and organizations' well-being. Some of these negative outcomes include problems with mental and physical health, cognitive functioning, job satisfaction, organizational commitment, turnover intentions, productivity, absenteeism, healthcare costs, and service quality (Melamed et al. 2006; Salvagioni et al. 2017; Alarcon, 2011; Lee and Ashforth, 1996; Bakker et al. 2014; Taris, 2006). Hassard et al. (2018) found that healthcare costs, decreased productivity, and staff turnover contribute significantly to burnout's substantial financial consequences.

We argue that the adoption of AI in the workplace will increase employee burnout based on the JD-R model, the conservation of resources (COR) theory, and the technostress model (Tarafdar et al. 2007).

First, the JD-R model states that job demands and job resources are the two main categories of job characteristics and that they interact to influence employee well-being outcomes, including burnout (Bakker and Demerouti, 2017). Job demands require mental and physical exertion from the worker, which might negatively affect their health (Demerouti, Bakker, Nachreiner, and Schaufeli, 2001). AI adoption can be seen as a job demand because it brings about new problems and complexities that require employees to acquire new skills, adjust to new work processes, and collaborate with AI systems (Makridis and Mishra, 2022; Pereira et al. 2023; Uren and Edwards, 2023). Furthermore, workers may feel pressured to work faster and more efficiently if AI systems are implemented in the workplace (Berente et al. 2021; Chen et al. 2023), and stress and fatigue, two hallmarks of burnout, might worsen as a result of the increased workload (Maslach et al. 2001). Employees may also face additional psychological expenses due to job demands, such as the need to constantly learn and improve their skills to remain relevant in their professions (Dwivedi et al. 2021; Zitar et al. 2023).

Second, the COR theory (Hobfoll, 1989) supports the connection between AI adoption and employee burnout. Resources comprise the things, traits, circumstances, and energy that an individual values; according to this theory, people work hard to acquire, keep, and safeguard their resources (Hobfoll, 2001). According to Karasek (1979) and Ryan and Deci (2000), AI can undermine employees' resources, including their confidence, independence, and job stability. Employees may suffer from burnout if they feel emotionally and mentally drained from worrying about losing these resources as a result of AI implementation (Hobfoll, 2001).

Third, the technostress model (Tarafdar et al. 2007) further clarifies the association between technology adoption and employee well-being. Technostress is the stress experienced by individuals due to the use of information and communication technologies (ICTs) in the workplace (Tarafdar et al. 2019). The adoption of AI technologies can be viewed as a specific instance of ICT implementation; thus, the technostress framework can be applied to understand AI's impact on employee burnout. Tarafdar et al. (2007) identified five key technostress creators:

techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. These technostress creators can manifest during AI adoption, leading to increased stress and burnout among employees (Khedhaouria and Cucchi, 2019). Specifically, techno-overload occurs when AI technologies increase workload and accelerate work pace, compelling employees to work more intensively (Borle et al. 2021). Techno-invasion refers to the erosion of the boundaries between one's work and personal life due to constant connectivity and availability expectations associated with AI systems (Tarafdar et al. 2007). Techno-complexity arises when employees find AI technologies difficult to understand and use, causing feelings of inadequacy and frustration (Tarafdar et al. 2011). Techno-insecurity is the fear of job loss or displacement due to AI, while techno-uncertainty denotes the continual changes and upgrades in AI technologies that require employees to adapt and acquire new skills regularly (Khedhaouria and Cucchi, 2019). In light of these arguments, the following hypothesis is proposed.

Hypothesis 1: AI adoption in an organization will increase burnout.

AI adoption and job stress. This paper suggests that AI adoption in an organization will increase job stress among employees. Job stress is a complex concept that encompasses the mental, emotional, and physical responses that workers display when confronted with challenges at work that are too difficult for them to handle (Lazarus and Folkman, 1984). When people face substantial pressure, difficulties, and demands at work, it can lead to negative bodily reactions as well as psychological strain (Ganster and Rosen, 2013).

We propose that the adoption of AI in an organization will increase job stress among employees by drawing on the JD-C) model (Karasek, 1979) and the person-environment (P-E) fit theory (Edwards et al. 1998).

First, according to the JDC model, job stress is caused by the interaction between job demands and job control. Workload, time constraints, and role conflicts are all examples of psychological stressors that employees face on the job (Karasek and Theorell, 1990). Conversely, job control is defined as the degree to which workers can exercise agency and competence in their work (Karasek, 1979). High job demands, coupled with a lack of control over those demands, increase job-related stress, according to the JD-C model (Häusser et al. 2010). One interpretation of AI's widespread use in an organization is that it will increase the demands imposed on human workers. When AI technologies are implemented, personnel are typically required to learn new skills, adjust to different work processes, and work with AI systems (Pereira et al. 2023; Zitar et al. 2023). As workers try to adapt to the new demands imposed by AI, they may find themselves under stricter time and effort constraints (Bankins et al. 2024; Pereira et al. 2023). Role ambiguity and conflict may also arise from AI systems' complexity and opaqueness as workers try to make sense of their evolving duties in relation to AI (Bankins et al. 2024; Pereira et al. 2023).

At the same time, AI adoption could make workers feel that they have less control over their jobs. As AI systems take over tasks and decision-making roles previously performed by humans, employees might experience a reduction in autonomy and decision-making power (Budhwar et al. 2022). The opaque nature of many AI algorithms can further erode employees' sense of control, as they may find it challenging to understand and influence the outcomes generated by these systems (Shrestha et al. 2021). Furthermore, when AI is implemented in the workplace, individuals may experience heightened job stress in line with the JD-C model's description of higher job expectations and lower job control.

Secondly, the P-E fit theory supports the idea that AI adoption can increase stress in the workplace. In this view, stress develops whenever an individual's skills, needs, and values, for example, do not align with what is required or provided by their workplace (Edwards et al. 1998). The widespread use of AI can lead to a skills gap between workers' present abilities and the abilities required by the technology (Makarius et al. 2020). A skills gap could emerge, adding to employee stress, as AI systems are always evolving and requiring continuous learning and adaptation (Nam, 2019). Another issue with AI adoption is that it can make workers feel less empowered than they actually are (Pereira et al. 2023). Workers may feel powerless because their desire for control conflicts with the reality of their work environment, especially as AI takes over decision-making and limits employees' discretion. According to the P-E fit theory, this misalignment can intensify job stress (Edwards et al. 1998).

Thirdly, the socio-technical systems theory (Trist and Bamforth, 1951) highlights the link between AI adoption and job stress. This theory emphasizes that an organization's social and technological subsystems must be aligned to improve employee performance and well-being (Baxter and Sommerville, 2011). A new set of tools, methods of operation, and criteria for making decisions are created by the introduction of AI (Vrontis et al. 2022). Workers may find that their needs conflict with those of the AI-enhanced workplace if the social subsystem—which comprises elements like job responsibilities, abilities, and interpersonal relationships—is not properly adjusted to the new technical subsystem (Pereira et al. 2023; Zitar et al. 2023). Because of this misalignment, workers may experience more job stress as they try to adapt to their new positions, learn necessary skills, and deal with the social effects of AI adoption (Shrestha et al. 2021).

Hypothesis 2: AI adoption in an organization will increase job stress.

Job stress and employee burnout. We argue that job stress will increase burnout among employees based on the COR theory (Hobfoll, 1989), the transactional model of stress and coping (TMSC; Lazarus and Folkman, 1984), and the JD-R model (Demerouti et al. 2001).

To begin, according to the COR theory, people work hard to acquire, keep, defend, and cultivate resources that they value. Things, qualities, circumstances, or energies that an individual values or that help them acquire more important resources are examples of resources (Hobfoll et al. 2018). Individuals experience stress when they are at risk of losing resources, actually lose resources, or fail to acquire resources after making substantial investments (Hobfoll, 2001). Workplace stress can be viewed as a condition of diminished resources. According to Bakker and Demerouti (2017), workers experience high levels of workplace stress because they are being asked to do more with less. Emotional and physical tiredness, as well as mental stress, may be signs of resource depletion (Alarcon, 2011). Burnout can develop after a long period of work under stressful conditions and resource scarcity (Hobfoll et al. 2018).

Second, according to the TMSC, people experience stress when they feel like they lack the coping resources necessary to meet the demands of a scenario. This suggests that cognitive appraisal and coping mechanisms are integral parts of the transactional process through which an individual experiences stress (Lazarus, 1999). Workplace stress is more common among workers who believe their workload exceeds their ability to cope compared to those who do not hold this belief (Goh et al. 2015). The essential component of burnout is the physical, emotional, and mental depletion created by prolonged exposure to job stress (Maslach et al. 2001). According to the TMSC, burnout can occur when

workers' emotional and cognitive resources are depleted due to an inability to cope with job pressures (Guthrie et al. 2020). This is in line with the COR theory's supposition that depletion and loss of resources lead to burnout (Hobfoll et al. 2018).

Third, the JD-R model shows how stress at work can lead to burnout. Job demands and job resources are the two main branches of job characteristics (Demerouti et al. 2001). Job demands comprise the social, organizational, and physically demanding factors of a job that cause one to incur physiological and psychological expenses over time (Bakker and Demerouti, 2007). High levels of emotional and mental strain, as well as time constraints, are examples of demands in the workplace (Bakker et al. 2014). Meanwhile, job resources are the physical, mental, social, and organizational parts of a job that help workers accomplish their goals, cope with stress, and develop themselves professionally and personally (Bakker and Demerouti, 2007). Social support, autonomy, and performance evaluation are examples of job resources (Van der Heijden et al. 2019). Worker strain and burnout are both predicted by the JD-R model, which states that workers are more likely to experience the former when job demands are high and job resources are low (Demerouti et al. 2001). Burnout is characterized by emotional, mental, and physical tiredness; it can be caused by job stress, which occurs when demands are high and resources are scarce (Maslach et al. 2001).

Hypothesis 3: Job stress will increase burnout.

The mediating role of job stress in the relationship between AI adoption and burnout. Examining how work stress mediates the association between AI adoption in an organization and burnout is one of the main goals of this study. By combining the JD-R model, the COR theory, and the TMSC, we expect job stress to function as a mediator in the AI adoption-burnout link.

First, employee well-being and organizational outcomes are affected by the interplay between job demands and job resources, which are classified according to the JD-R model (Bakker and Demerouti, 2017). AI adoption in an organization will create a need for more people to learn and adapt to new technology, more work to accomplish, and possibly more role ambiguity (Bankins et al. 2024; Pereira et al. 2023). The JD-R model postulates that burnout and other negative effects may occur when work demands exceed available resources.

Secondly, according to the COR theory, stress on the job mediates the link between AI adoption and burnout. According to this theory, people work hard to get what they want and keep what they have (Hobfoll et al. 2018). Workers' confidence, independence, and job stability are among the resources that can be jeopardized by the introduction of AI. Workers may suffer from emotional and mental exhaustion and burnout if they worry that AI integration will cost them their resources (Hobfoll, 2001).

Finally, the function of job stress as a mediator between AI adoption and burnout is further explained by the TMSC. This paradigm proposes that when people face a challenge, like adopting AI, they carry out a cognitive appraisal to determine how serious the challenge is and what resources they possess for dealing with it (Lazarus and Folkman, 1984). Workers may feel more pressure at work if they worry that AI adoption may undermine their job stability, work identity, or ability to execute their jobs well and if they do not think they can deal with these issues. Employees may suffer from burnout if they constantly experience a level of stress that they cannot handle.

In light of the arguments outlined above, we provide the following hypothesis.

Hypothesis 4: Job stress will mediate the association between AI adoption in an organization and burnout.

The moderating influence of self-efficacy in AI learning on the link between AI adoption and job stress. We hypothesize that the increasing effect of AI adoption on work stress will be weakened by an individual's confidence in their AI learning capabilities. In this context, self-efficacy in AI learning is a person's confidence in their ability to learn about and work with AI (Bandura, 1977). More specifically, this context-specific construct signifies how confident a person is in their ability to interact with AI systems, understand AI ideas, and effectively use AI tools (Kim and Kim, 2024). The concept of self-efficacy in AI learning originates from Bandura's SCT (Bandura, 1986). This theory posits that how someone perceives their talents impacts their motivation, actions, and achievement in a certain area. One's perceptions of their ability to learn AI can influence how much time and effort people are prepared to devote to AI-related tasks, how well they handle setbacks, and how effectively they practice what they have learned (Kim and Kim, 2024).

The link between AI adoption and employee job stress can be better understood by delving into the moderating effect of employee self-efficacy in AI learning. Based on the TMSC and SCT, we propose that the effect of the adoption of AI on job stress will be weakened if employees have faith in their capacity to understand and utilize the technology.

First, the SCT proposes that an individual's self-efficacy—their confidence in their abilities to carry out the actions that will lead to a desired outcome—strongly influences their reasoning, drive, and emotions (Bandura, 1997). The term “self-efficacy in AI learning” is used in the context of AI adoption to describe an employee's belief in their capacity to acquire and use knowledge and skills pertaining to AI (Bandura, 1986). Individuals with higher self-efficacy are less stressed, more inclined to perceive setbacks as learning experiences, and more willing to persevere in the face of adversity (Bandura, 1997). Furthermore, the TMSC sheds light on how self-efficacy factors into stress evaluation (Lazarus and Folkman, 1984). According to this model, people perform a cognitive assessment when confronted with a possible stressor, such as the implementation of AI at work, to determine the gravity of the situation and how well they can cope (Lazarus and Folkman, 1987). Concerning AI, employees who have faith in their abilities to learn and adapt to new technologies are likely to view AI adoption as a task they can accomplish rather than an overwhelming danger.

Workers who have high levels of self-efficacy in AI learning also have faith in their abilities to learn and use AI efficiently (Bandura, 1997). According to SCT, this group is more likely to see the widespread use of AI as a chance for professional and personal development rather than a danger (Bandura, 2012). These workers are always looking for new ways to improve their knowledge and abilities and are quick to adopt new technology (Chae et al. 2019). The demands of AI adoption can be better managed by workers who believe in their capability to learn AI than those who do not hold this belief.

Additionally, the TMSC (Lazarus and Folkman, 1987) suggests that these individuals can perceive the adoption of AI as a manageable stressor during the main assessment process since they are confident in their ability to acquire the essential abilities needed to work with AI. Their coping resources, including their AI learning capacities, are likely to be deemed appropriate during the secondary evaluation process to fulfill the demands of the situation. Workers who have faith in their abilities to learn AI are relatively unlikely to feel threatened by the adoption of AI in the workplace. This is because they are confident in their ability to adapt and profit from the process.

For example, if an organization uses AI to power its CRM systems, workers with high self-efficacy in AI learning could view the situation as a chance to hone their customer service skills

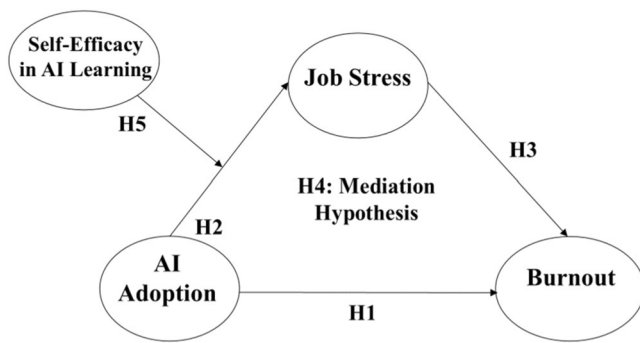


Fig. 1 Theoretical model.

while also effectively using the data AI provides to craft unique encounters for each client. These workers will also be more inclined to take part in training programs, ask for help when they need it, and try using new CRM technologies in order to reach their full potential. Moreover, they can adapt to new technology with less stress than other workers since they actively seek out resources to develop their AI competencies and engage in proactive learning activities. As a result, they do not worry excessively about failing to meet expectations and are confident in their ability to use an AI-powered CRM system to improve their company's performance.

This situation is reversed when workers lack self-efficacy in their abilities to understand and utilize AI-related information (Bandura, 1997). SCT claims that these people are more prone to view AI adoption as a threat to their job security and competence, owing to their heightened anxiety and tension (Bandura, 2012). They might act in ways that prevent them from learning, resist learning opportunities, and have trouble adjusting to new technologies (Charness and Boot, 2016). In addition, workers who do not believe in their abilities to learn AI might struggle to meet the challenges of AI implementation. As a result, when a company implements AI systems, these workers are likely to feel stressed because they are not prepared to deal with the new responsibilities and obstacles that will inevitably arise.

This is supported by the TMSC's suggestion that employees who lack confidence in their ability to acquire AI are likely to view AI adoption as a stressful event that they cannot manage during the primary assessment process (Lazarus and Folkman, 1987). They may conclude that their coping resources, especially their AI learning capabilities, are inadequate to handle the situation's demands during the secondary appraisal process. Individuals who lack confidence in their ability to learn AI face increased workplace stress, difficulties adjusting to their organizations' AI adoption practices, and uncertainty regarding their future with the company (Bankins et al. 2024; Pereira et al. 2023).

For instance, employees who do not think they are good at learning how to use AI could feel intimidated by the new CRM tools that an organization installs. They may be resistant to training sessions, hesitant to use new customer relationship management systems, and worried about losing their jobs to AI (Meyer and Hünefeld, 2018). As a result, these workers will feel increased stress on the job as they worry about failing to achieve the new standards set by the AI-powered CRM system and their inability to adjust to it.

The following hypothesis is based on the above theoretical considerations:

Hypothesis 5: Self-efficacy in AI learning will moderate the link between AI adoption in an organization and job stress such that the positive association between AI adoption and job stress

will be weaker for employees with high self-efficacy in AI learning compared to those with low self-efficacy.

Figure 1 illustrates the conceptual model utilized in this study, which depicts the hypothesized relationships between AI adoption, job stress, and burnout, as well as the moderating role of self-efficacy in AI learning.

Method

Participants and procedure. A group of working adults in South Korea, all in their 20s or older, from different companies participated in the present study. A three-wave time-lagged research design was used, in which participants participated at three separate times. A famous internet research organization with a respondent pool of about 5.45 million people supported the recruitment process. Participants were asked to verify their work status when they registered online, and the platform identified participants using their email addresses or mobile phone numbers. Evidence from earlier studies supports the use of online surveys to attract a representative sample of a population (Landers and Behrend, 2015).

The constraints of cross-sectional research methodologies were addressed by collecting data from actively employed persons in South Korean organizations at three separate times. The researchers used a digital infrastructure to monitor how actively participants engaged with the survey. This helped to guarantee that participation remained consistent throughout the study. Data were collected at intervals of five and six weeks, and each survey window was two or three days long, thus providing respondents sufficient time to complete the survey. The organization used Geo-IP limitation traps and other data integrity safeguards to detect and prevent overly fast answers, which maintained the high quality of the research results.

Registrants were invited to participate in this research by the survey firm. The researchers reassured prospective participants that their participation was optional and promised to keep participants' answers private and use them only for research purposes. All participants gave their informed consent, and we followed all applicable ethical guidelines. Financial incentives ranging from \$8.00–\$9.00 were offered to participants.

The researchers used stratified random sampling to choose a cohort at random from several strata based on demographic and occupational factors such as age, gender, education level, and industry. This helped to minimize sampling bias. The survey firm tracked respondents' interactions on several digital platforms to make sure the same people participated in all three waves of the poll.

Across the three waves, 803 workers took part in the first wave, 571 replied in the second wave, and 418 replied in the third wave. Surveys that did not contain all necessary information were not included in the final data set. The 416 participants (51.81% of the total) who filled out all three questionnaires comprised the study's final sample (see Table 1). G*Power was used for statistical analysis, and the proposal of Barclay et al. (1995) for a minimum of 10 instances per variable was followed, leading to the calculation of the sample size. Figure 2 presents a flow chart of the methodology employed in this study, illustrating the sequential steps of our research process, from participant recruitment to data analysis.

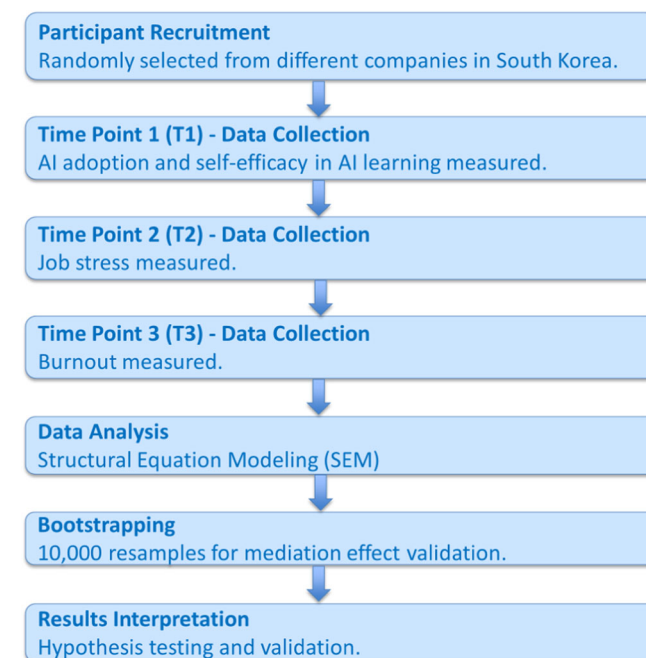
Measures. First, data related to AI adoption and self-efficacy in AI learning were collected. Participants reported their levels of job stress at the second time point. Information regarding the severity of burnout was gathered at the third interval. We used 5-point Likert scales with multiple items to evaluate each variable.

Table 1 Descriptive characteristics of the sample.

Characteristic	Percent
<i>Gender</i>	
Men	51.9
Women	48.1
<i>Age (years)</i>	
20–29	21.2
30–39	21.9
40–49	29.1
50–59	27.9
<i>Education</i>	
High school or below	12.3
Community college	19.2
Bachelor's degree	56.5
Master's degree or higher	12.0
<i>Position</i>	
Staff	41.3
Assistant Manager	17.1
Manager or Deputy General Manager	23.8
Department/General Manager or Director and above	17.8
<i>Firm Size</i>	
1–9 employees	15.1
10–29 employees	16.6
30–49 employees	10.1
50–99 employees	14.9
100–149 employees	8.4
150–299 employees	7.5
300–449 employees	4.1
500–999 employees	7.0
1000–4999 employees	9.9
Above 5000 employees	6.5
<i>Industry type</i>	
Manufacturing	22.8
Services	13.2
Construction	12.2
Health and welfare	16.3
Information services and telecommunications	9.1
Education	15.4
Financial/Insurance	2.6
Consulting and advertising	0.5
Other	7.7

AI adoption (point in time 1, as reported by workers). We used five items modified from scales established in earlier research to measure the level of AI adoption in an organization (Chen et al. 2023; Cheng et al. 2023; Pan et al. 2022). Specifically, the following items were used: “Our organization uses artificial intelligence technology in its human resources management system,” “Our organization uses artificial intelligence technology in its production and operations management systems,” “Our organization uses artificial intelligence technology in its marketing and customer management systems,” “Artificial intelligence technology is used in our organization’s strategic and planning systems,” and “Artificial intelligence technology is used in our organization’s financial and accounting systems.” A Cronbach’s alpha value of 0.949 was reported.

Self-efficacy in AI learning (point in time 1, as reported by workers). We used a four-item scale from prior research that adapted Bandura’s self-efficacy scale for use in AI learning (Bandura, 1986). The scale was established by prior research (Kim and Kim, 2024). The following items were considered: “I am confident in my ability to learn artificial intelligence technology appropriately in my work,” “I am able to learn artificial intelligence technology to perform my job well, even when the situation is challenging,” “I can develop my competencies needed for my

**Fig. 2** Methodology Flow Chart.

job through AI technology learning,” and “I will be able to learn important information and skills from my AI training.” A Cronbach’s alpha value of 0.936 was reported.

Job stress (point in time 2, as reported by workers). The survey included six items from the job stress scale, which was developed by modifying previous scales (DeJoy et al. 2010; Motowidlo et al. 1986) to measure job stress. The utilized items include the following: “I feel a great deal of stress because of my job,” “I experience many stressful events at work,” “My job is quite stressful,” “I feel frustrated at work,” “I feel tense or anxious at work,” and “I feel angry or irritated at work.” A Cronbach’s alpha value of 0.913 was reported.

Burnout (point in time 3, as reported by workers). The six items from the Maslach Burnout Inventory (Maslach et al. 1997, 2001) were used to assess the severity of burnout among employees. The items used include the following: “I feel emotionally drained from my work,” “By the time I get home from work, I am mentally and physically exhausted,” “I feel like my work is mentally and physically draining my energy,” “I have become less enthusiastic about my work,” “I feel like I’ve reached my limits with my work,” and “I feel tired when I get up in the morning and have to face another day on the job.” A Cronbach’s alpha value of 0.891 was reported.

Control variables. We included employee tenure, gender, position, and education as control variables, as prior research indicates that these factors can influence burnout (Maslach et al. 1997, 2001). We collected data for these control variables in the first survey. The literature suggests including gender, education level, position, and tenure as control variables when studying burnout. These control variables were considered to help us interpret the main variables more clearly and decrease the bias caused by omitted variables.

Table 2 Correlation among research variables.

	Mean	SD	1	2	3	4	5	6	7
1. Gender_T1	1.48	0.50	–						
2. Education_T1	2.68	0.84	–0.06	–					
3. Tenure_T1	67.84	74.03	–0.07	0.05	–				
4. Position_T1	2.44	1.52	–0.36**	0.29**	0.33**	–			
5. AI_T1	2.28	1.04	–0.15**	0.12*	0.05	0.07	–		
6. SE_T1	3.38	0.86	–0.09	0.14**	0.02	0.02	0.18**	–	
7. JS_T2	2.87	0.87	–0.06	0.14**	–0.08	0.02	0.20**	–0.11*	–
8. BO_T3	2.99	0.82	0.03	0.06	–0.14**	–0.05	0.14**	0.08	0.52**

SD means standard deviation, AI means artificial intelligence adoption in an organization, SE means self-efficacy in AI learning, JS means job stress, and BO means burnout. As for gender, males are coded as 1, and females are coded as 2. As for position, general manager or higher are coded as 5, deputy general manager and department manager are coded as 4, assistant manager is coded as 3, clerk is coded as 2, and others below clerk are coded as 1. As for education, “below high school diploma” level is coded as 1, “community college” level is coded as 2, “bachelor’s” level is coded as 3, and “master’s degree or more” level is coded as 5.

* $p < 0.05$; ** $p < 0.01$.

Statistical analysis. After data were collected, a Pearson correlation analysis was performed in the SPSS 28 software suite to investigate the connections between the research variables. Per the two-stage procedure proposed by Anderson and Gerbing (1988), the research technique incorporated a measurement model and a structural model. Confirmatory factor analysis (CFA) was used to validate the measurement model. After that, the structural model was checked with AMOS 26 software’s moderated mediation model analysis, with the ML estimate approach utilized in accordance with SEM principles.

Several fit indices were used to assess how well the model matched the empirical data. These included the comparative fit index (CFI), the Tucker–Lewis index (TLI), and the root mean square error of approximation (RMSEA). Values above 0.90 for CFI and TLI and values below 0.06 for RMSEA were considered acceptable, in line with the norms given by the academic community. Bias was accounted for by utilizing a 95% confidence interval (CI), which was calculated using bootstrapping methodology, thus backing up the mediation hypothesis. A non-zero CI implies a statistically significant indirect effect at the 0.05 level, according to Shrout and Bolger (2002).

Results

Descriptive statistics. Our findings reveal strong relationships between AI adoption, self-efficacy in AI learning, job stress, and burnout. Table 2 displays the findings of the analysis.

Measurement model. We checked the measurement model’s goodness-of-fit and the four primary study variables’ discriminant validity using CFA. The four-factor model was compared with various alternative models using chi-square difference tests. These models included a three-factor model (χ^2 (df = 184) = 1792.555, CFI = 0.760, TLI = 0.727, and RMSEA = 0.145), a two-factor model (χ^2 (df = 186) = 3102.000, CFI = 0.566, TLI = 0.510, and RMSEA = 0.194), and a one-factor model (χ^2 (df = 187) = 4431.832, CFI = 0.368, TLI = 0.290, and RMSEA = 0.234). A series of chi-square difference tests were implemented to find the best model. Fit indices for the four-factor model indicated superior fit, with a chi-square value (df = 181) = 395.219, CFI = 0.968, TLI = 0.963, and RMSEA = 0.053. The four-factor model correctly discriminated between the study variables.

Structural model. We tested our assumptions using a moderated mediation model that we built. This concept contains elements of mediation and moderation. Job stress acts as a mediator between AI adoption and burnout, and self-efficacy in AI learning reduces the influence of AI adoption on job stress.

An interaction term was generated in this moderation framework by multiplying the two variables of AI adoption and self-efficacy in AI learning. We mean-centered the variables before creating the interaction term to address potential multi-collinearity. Brace, Kemp, and Snelgar (2003) found that centering processes help decrease multi-collinearity and prevent correlations from diminishing, which strengthens the validity of moderation analysis.

Brace et al. (2003) recommend calculating variance inflation factor (VIF) values and tolerances to evaluate possible multi-collinearity. With tolerance indices of 0.967, AI adoption and self-efficacy in AI learning both had VIF values of 1.034. Thus, the data suggest that AI adoption and self-efficacy in AI were unaffected by multi-collinearity. This is supported by the tolerance values exceeding 0.2 and VIF values below 10 (Brace et al. 2003).

Findings of the mediation evaluation. The best-fitting model was determined by comparing a partial mediation model with a full mediation model using a chi-square difference test. The only difference between the partial and complete mediation models was that the latter did not include the causal relationship between AI adoption and burnout. Both models showed good fit indices, with $\chi^2 = 501.018$ (df = 212), CFI = 0.948, TLI = 0.938, and RMSEA = 0.057 for the full mediation model and $\chi^2 = 500.972$ (df = 211), CFI = 0.948, TLI = 0.938, and RMSEA = 0.058 for the partial mediation model.

However, the chi-square difference between the models ($\Delta\chi^2$ [1] = 0.046, $p > 0.05$, non-significant) demonstrated that the full mediation model was more suitable. This finding implies that AI adoption affects burnout indirectly through job stress rather than having a direct impact. This study incorporated control variables related to burnout, including gender, education level, job title, and tenure. Except for tenure, all control factors were found to be statistically insignificant ($\beta = -0.097$, $p < 0.05$).

Hypothesis 1 was rejected since the partial mediation model revealed that AI adoption in an organization was not significantly related to burnout ($\beta = 0.010$, $p > 0.05$). With a non-significant coefficient, the partial mediation model—which showed a direct correlation between AI adoption and burnout—solidified the preference for the full mediation model, which was approved. This result, along with the improved fit indices, confirmed that the full mediation model is better than the partial one. Therefore, we rejected Hypothesis 1 and concluded that job stress is a likely mediator between AI adoption and burnout.

Hypothesis 2 states that the adoption of AI significantly increases job stress ($\beta = 0.286$, $p < 0.001$), and Hypothesis 3 states that burnout is significantly increased by job stress ($\beta = 0.568$,

$p < 0.001$). The results corroborate both claims (see Fig. 3 and Table 3).

Bootstrapping. Following the methods reported by Shrout and Bolger (2002), we used a bootstrapping technique with a large sample size of 10,000 to test Hypothesis 4, which states that job stress mediates the association between AI adoption and burnout. The recommendation of Shrout and Bolger (2002) states that in order for the average indirect effect to be deemed statistically significant, the 95% bias-corrected CI must not include 0.

This research employed a bootstrapping approach to investigate the mediation effect of job stress on the link between AI adoption and burnout, as proposed in Hypothesis 4. The mediation effect would be considered statistically significant if the average effect's 95% bias-corrected CI is not 0. Job stress is a statistically significant mediator, as the data demonstrate a CI that excluded 0 (95% CI = [0.102, 0.230]). Thus, Hypothesis 4 was accepted. Table 4 presents the full path from AI adoption to burnout, including the direct, indirect, and total effects.

Moderation evaluation findings. This study aimed to determine whether one's belief in their ability to learn AI affects the relationship between AI adoption and job stress. This was examined by constructing an interaction term by mean-centering the variables AI adoption and self-efficacy in AI learning. The examination showed that this interaction term was statistically significant ($\beta = -0.279$, $p < 0.001$). This finding shows that one's belief in their ability to learn AI acts as a moderator, weakening the influence of AI adoption on job stress. This result supports Hypothesis 5 (Fig. 4).

Discussion

This research aimed to answer several questions about the associations between AI adoption in the workplace, job stress, and burnout, with self-efficacy in AI learning serving as a moderator. Organizations that want to manage members' well-being in the

face of technological change should consider the psychological consequences of AI adoption at work. This research gives vital insights into those implications.

The findings presented in Table 5 align with and extend previous research in several key areas. For instance, based on the review by Bankins et al. (2024), our findings on the indirect impact of AI adoption on burnout through job stress, as well as the focus on self-efficacy in AI learning, complements the work of Marikyan et al. (2022) on human-AI collaboration. Furthermore, our investigation of self-efficacy as a moderating factor builds upon Ding et al.'s (2021) exploration of workers' attitudes toward AI. Moreover, our study contributes to the literature by examining the connections among AI adoption, job stress, burnout, and self-efficacy in AI learning in a comprehensive framework, thus providing a more nuanced understanding of these relationships in the context of organizational AI adoption.

Hypothesis 1 proposed that AI adoption in an organization increases employee burnout. However, the results did not support this hypothesis, as the direct association between AI adoption and burnout was non-significant. This finding is surprising, given the growing concern about the potential harmful influence of AI on employee well-being (Dwivedi et al. 2021). Nevertheless, this result highlights the importance of considering the complex mechanisms through which AI adoption may affect employee outcomes, rather than assuming a simple direct relationship.

Hypothesis 2 predicted that implementing AI in the workplace would increase job stress among workers. According to the JD-R model, high job demands, such as those that could be generated by AI adoption, can create stress, and the current finding is in line with this theory. AI can increase stress in the workplace by posing new problems for workers to solve, such as the need to learn new technologies, uncertainties about responsibilities, and increased workload (Brougham and Haar, 2018).

The findings also support Hypothesis 3, which posited that job stress increases employee burnout. This finding is in line with the JD-R's claim that burnout and tiredness might be the outcomes of long-term exposure to stressful work environments (Bakker and Demerouti, 2017). Employees may be more prone to burnout symptoms, such as emotional tiredness, cynicism, and diminished personal accomplishment, due to the increasing job stress caused by AI adoption (Maslach et al. 2001).

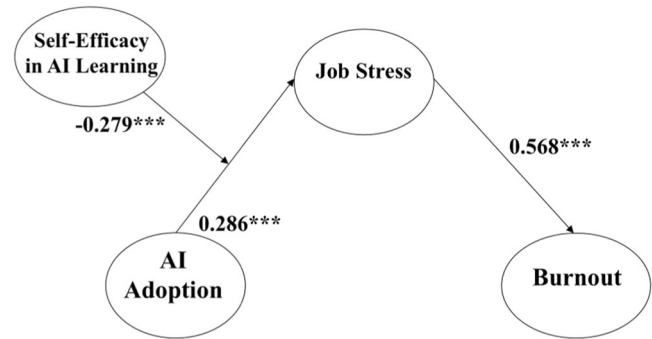


Fig. 3 Coefficient Values of Our Research Model (** $p < .001$. All values are standardized).

Table 4 Direct, indirect, and total effects of the final research model.			
Model (Hypothesis 4)	Direct effect	Indirect effect	Total effect
AI adoption → Job stress → Burnout	0.000	0.163	0.163
All values are standardized.			

Table 3 Results of structural model.					
Hypothesis	Path (relationship)	Unstandardized estimate	SE	Standardized estimate	Supported
1	AI adoption → Burnout	0.008	0.038	0.010	No
2	AI adoption → Job stress	0.235	0.041	0.286***	Yes
3	Job stress → Burnout	0.538	0.051	0.568***	Yes
5	AI adoption × self-efficacy in AI learning	−0.246	0.043	−0.279***	Yes
Estimate indicates standardized coefficients. SE means standard error. The coefficient value of the path from AI adoption to burnout (H1) was in the partial mediation model, which was not accepted as a final model.					
*** $p < 0.001$.					

Furthermore, the results support Hypothesis 4, which postulated that job stress mediates the association between AI adoption and employee burnout. Adopting AI did not affect burnout directly, but it significantly impacted burnout indirectly through increased job stress. This conclusion highlights the significance of investigating how the implementation of AI can affect the welfare of employees. Adopting AI can increase stress levels, which can cause burnout because it creates new demands and challenges in the workplace.

According to Hypothesis 5, employees with higher levels of self-efficacy in AI learning exhibit a less positive association between AI adoption and job stress. This link was expected to be moderated by self-efficacy in AI learning. The results show that self-efficacy in AI learning mitigated the raising effect of AI adoption on job stress, thus supporting this hypothesis. The fundamental ideas underlying SCT are consistent with this discovery since it highlights the power of self-efficacy beliefs in molding how people react to difficulties and pressures. Workers with high levels of self-confidence may view the implementation of AI as less daunting and more controllable compared to other

workers, reducing the likelihood that AI implementation will be a source of stress.

Theoretical implications. The current paper has some crucial theoretical implications. Firstly, this paper provides a thorough theoretical framework for understanding the complex relationship between AI adoption and employee burnout by combining the JD-R model with SCT. The JD-R model provides an excellent starting point for investigating the function of work stress as a moderator between AI adoption and burnout, as it posits that resources and job demands interact to impact organizational outcomes and employee well-being (Bakker and Demerouti, 2017). This study expands the JD-R model’s applicability to the context of AI adoption by offering a nuanced understanding of the psychological mechanisms linking AI adoption to burnout. It does this by conceptualizing AI adoption as a distinct job demand requiring employees to adapt to new technologies, obtain new skills, and manage increased complexity and uncertainty (Chen et al. 2023; Dwivedi et al. 2021; Makridis and Mishra, 2022; Uren and Edwards, 2023).

In addition, this study provides a new perspective on the moderating effect of self-efficacy in AI learning by considering SCT, which highlights the influence of self-efficacy on people’s beliefs, behaviors, and coping mechanisms (Bandura, 1986). According to SCT, one’s self-efficacy (i.e., one’s confidence in their ability to accomplish a task) has the greatest impact on one’s goal-setting, stress-management, and challenge-taking strategies (Bandura, 1997). This study expands the applicability of SCT to the context of AI adoption and employee resilience by highlighting that self-efficacy in AI learning is a personal resource that can buffer the harmful impacts of AI adoption on employee well-being. The integration of the JD-R model and SCT offers a holistic theoretical perspective for understanding the complex interplay between AI adoption, job stress, self-efficacy, and burnout, thereby enhancing theory development in organizational psychology.

Second, by viewing AI adoption as a unique and multifaceted job demand, this research adds to the body of literature on job demands and resources. This study investigated the demands of AI adoption, which include learning and adapting to new AI technologies, managing the complexities of human–AI collaboration, and addressing uncertainties about how AI will affect job

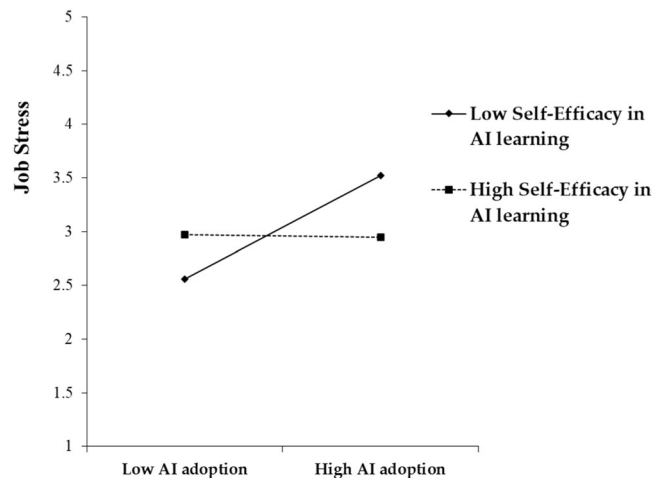


Fig. 4 Moderating effect of self-efficacy in AI learning in the AI adoption–job stress link.

Table 5 Comparison of related research findings.			
Study	Focus	Key findings	Relation to our study
Marikeyan et al. (2022), Sowa et al. (2021), Tong et al. (2021)	Human-AI collaboration	- AI satisfaction increases job satisfaction and productivity. - Task-technology fit and AI quality improve performance.	We explore how these factors affect stress and burnout.
Pethig and Kroenung (2022), Keding and Meissner (2021), Candrian and Scherer (2022)	Perceptions of algorithmic vs. human capabilities	- AI perceived as more objective in decision-making. - Explores views on AI taking over human work.	We examine how these perceptions interact with self-efficacy in AI learning.
Ding (2021), Innocenti and Golin (2022)	Worker attitudes towards AI	- AI as challenge vs. hindrance stressor affects coping. - Focus on fear-based responses to AI.	We investigate how attitudes moderate AI adoption-stress relationship.
Wood et al. (2019), Glavin et al. (2021), Duggan et al. (2022)	AI in algorithmic management of platform work	- Examines AI for control and surveillance. - Worker responses in gig economy.	Informs our understanding of AI management practices’ impact on stress.
Fossen and Sorgner (2022), Egana-del Sol et al. (2022), Walkowiak (2021)	Labor market implications of AI use	- Impact on job growth and skill demand. - Differential effects on worker groups.	We extend to individual-level impacts on stress and burnout.

roles and responsibilities. Existing works have examined the effects of technology adoption on employee well-being (e.g., Meyer and Hünefeld, 2018). This study adds to the existing body of knowledge by offering a comprehensive analysis of AI-related job demands and their effects. It also highlights the significance of considering the distinct features of AI technologies when evaluating their influence on employee well-being. An understanding of the importance of AI-specific demands and how they may affect employee stress and burnout is fundamental for theoretical progress in organizational psychology and AI adoption (Makarius et al. 2020).

Third, this research adds to the previous literature on personal resources and employee resilience by highlighting the significant impact of AI learning self-efficacy as a moderator in the association between AI adoption and job stress. The current study explored the role of AI learning self-efficacy, which is a fresh and pertinent personal resource related to AI adoption. Existing works have acknowledged the significance of personal resources in reducing the harmful influence of job demands on workers' well-being (e.g., Xanthopoulou et al. 2007). The current research contributes to the literature on SCT by showing that employees who possess a strong belief in their capability to learn AI can deal with the difficulties and expectations associated with AI adoption. Therefore, organizations can reduce the negative impacts of AI adoption on well-being and increase employee resilience through AI training and development programs that raise self-efficacy (Pillai and Sivathanu, 2020). In addition to its substantial theoretical implications, this finding stresses the importance of further studies on the association between AI adoption and employee well-being as it pertains to other personal resources like resilience and adaptability.

Fourth, this study adds to the expanding literature on the mental health effects of AI adoption in the workplace by providing the first empirical examination of the association between AI adoption, job stress, and burnout. Research has shown that AI adoption could affect workers' well-being from a theoretical perspective (e.g., Bankins et al. 2024; Budhwar et al. 2022; Pereira et al. 2023). However, our study adds to the literature by providing empirical evidence that job stress mediates the association between AI adoption and burnout. This study provides a detailed explanation of the psychological processes of the relationship between AI and burnout by showing that adopting AI can raise job stress, which, in turn, increases burnout. Based on existing works (Bankins et al. 2024; Budhwar et al. 2022; Glikson and Woolley, 2020), this finding has significant theoretical implications and highlights the need for organizations to prioritize the well-being of their employees and proactively address the psychological challenges associated with AI implementation. This study also calls for more research on the long-term influences of AI adoption on organization outcomes and workers' well-being (Pereira et al. 2023). It also emphasizes the need to consider the unexpected consequences of AI adoption on workers' mental health.

Practical implications. Our results need to be carefully interpreted by top management teams, leaders, and practitioners, because of the significant practical implications they may have.

First, the current study highlights the significance of prioritizing the well-being of employees and proactively addressing the psychological issues associated with AI adoption. It also highlights the significance of taking a human-centered strategy to AI deployment (Budhwar et al. 2022; Glikson and Woolley, 2020). Because implementing AI can make workers more anxious on the job and more likely to experience burnout, companies need to devise plans to help their employees stay mentally healthy and

resilient while they implement AI. Companies can help relieve workers' concerns about AI by creating an environment that is welcoming to all employees, where stress management classes are available, and where employees feel safe speaking their minds (Budhwar et al. 2022; Pereira et al. 2023).

Leaders and upper-level management should also get workers' input about AI adoption by asking for their thoughts and opinions to make sure the technology is tailored to workers' abilities, expectations, and requirements (Bankins et al. 2024; Rai et al. 2019). Firms may help employees cope with the harmful influences of AI on their well-being by engaging them in decision-making and allowing them to shape the path of AI adoption (Meyer and Hünefeld, 2018). Leaders should be open and honest with their employees regarding the AI adoption process, including its aims, advantages, and possible obstacles. They should also let their employees know what steps are being taken to support them. Workers' worries about how AI may affect their jobs and responsibilities can be allayed through open and honest dialogue that fosters trust and minimizes uncertainty.

Second, this study highlights the significance of AI training and development programs in boosting members' self-assurance in their AI learning capabilities. This, in turn, will mitigate the harmful influences of AI adoption on stress and burnout in the workplace. Companies should put money into AI training programs that teach workers how to use AI effectively but also how to have a growth mindset and believe in themselves so they can thrive in a workplace driven by AI. Training programs should be designed with various employee groups' needs and ability levels in mind, thus providing a safe space for learning that promotes trying new things, receiving and acting on feedback, and constant improvement (Dwivedi et al. 2021). Furthermore, companies should help people maintain and improve their AI abilities over time since employees need to constantly learn and adapt to new technologies (Bankins et al. 2024; Pereira et al. 2023). Such efforts might include online learning platforms, chances for employees to learn from each other and share their knowledge, and rewards for employees who put in the effort to become AI-competent (Berente et al. 2021; Chen et al. 2023; Meyer and Hünefeld, 2018). Organizations that put money into AI training may assist their workers in thriving in a world where AI is the driving force behind many commercial decisions. This will boost their confidence in their capacity to master AI and encourage a growth mindset.

Third, the literature stresses the significance of aligning AI system design and implementation with employees' requirements, competencies, and well-being (Glikson and Woolley, 2020). Organizations can lessen AI's negative impact on worker stress and burnout by making sure the technology works in tandem with human talent rather than trying to supplant it (Makarius et al. 2020). In order to accomplish this, organizations must perform comprehensive job assessments (Rai et al. 2019) to identify processes and jobs that can be automated by AI and the abilities that workers will need to collaborate successfully with these systems. Furthermore, organizations should prioritize the health and well-being of their employees while developing AI systems. This includes adding capabilities that lessen the cognitive load, simplify processes, and supply the tools and resources needed to handle the demands of human-AI collaboration. Methods for dealing with AI-related mistakes or outliers should be clearly defined, and user-friendly interfaces should be implemented (Bankins et al. 2024; Dwivedi et al. 2021). Firms can foster a more positive and empowering work environment for their employees by developing AI systems that are tailored to their needs and skills.

Fourth, research stresses the need to continuously assess how AI implementation affects worker's well-being and organizational outcomes (Oksanen et al. 2022). Organizations must regularly

evaluate their AI implementation and make any required adjustments to keep up with the ever-changing AI landscape and make sure their strategies meet the needs of employees and the company (Bankins et al. 2024). This may require key performance indicators pertaining to creativity, quality, and productivity to be monitored and frequent surveys and focus groups with employees to be conducted to understand their thoughts on how the adoption of AI is affecting their well-being, stress, and burnout (Pillai and Sivathanu, 2020). In addition to measuring the technical performance of AI systems and their effect on employee engagement and well-being, organizations should set clear benchmarks to assess the success of their AI initiatives (Makarius et al. 2020). Organizations can improve their AI strategies, make data-driven decisions about future investments, and identify areas for improvement by regularly monitoring and assessing the impact of AI adoption.

Limitations and suggestions for future research. Although this paper enhances the knowledge of AI adoption's impact on employee well-being, it has certain limitations that present opportunities for further research in this field. First, although this study uses three-wave time-lagged data, it is fundamentally cross-sectional, which makes it difficult to draw any causality concerning AI adoption, job stress, and burnout. To better understand how these connections change over time, future research should use longitudinal techniques. By doing so, researchers can better explain the long-term effects of AI adoption on employee well-being and investigate potential reciprocal relationships between job stress and burnout.

Secondly, common method bias may have affected the results because the study utilized self-reported measures of job stress and burnout (Podsakoff et al. 2003). Future research should make use of objective metrics like cortisol levels, which are physiological markers of stress, or ratings given by supervisors, which are third-party evaluations of burnout. A combination of methods would be preferable for ensuring a more thorough evaluation of the mental and behavioral effects of AI implementation (Bankins et al. 2024; Pereira et al. 2023).

Third, while this study examined the mediating role of job stress in the relationship between AI adoption and burnout, it did not explore the specific job demands and resources that contribute to job stress in the context of AI adoption. Future research should investigate unique demands (e.g., techno-complexity, techno-uncertainty) and resources (e.g., AI-related training, technical support) in AI-driven work environments (Brougham and Haar, 2018). Identifying key job characteristics that shape employees' stress and burnout would enable organizations to develop targeted interventions to mitigate AI adoption's harmful influence on well-being.

Fourth, this research examined how self-efficacy in AI learning can decrease the detrimental influences of AI adoption on burnout and stress on the job. Employees' reactions to AI adoption may be impacted by other human qualities, like openness to new experiences and resilience (Khedhaouria and Cucchi, 2019). To better understand the factors that contribute to employee resilience and well-being in AI-enabled environments, future research should explore additional personal resources and individual differences in the relationships between AI adoption, job stress, and burnout (Meyer and Hünefeld, 2018).

Fifth, this study did not cover the possible benefits of AI adoption, such as enhanced productivity, innovation, and employee engagement. It is critical to address the problems and unforeseen effects of AI adoption, but it is just as important to look at the possibilities and advantages that AI technology can offer to organizations and their workers (Glikson and Woolley,

2020). Future research on the effects of AI adoption on organizational performance and employee well-being should follow a nuanced approach that considers both the upsides and the downsides of AI adoption. Organizations looking to maximize AI's benefits while minimizing its negative effects on the workforce will benefit greatly from this comprehensive perspective (Rai et al. 2019).

Sixth, we did not control for industry-specific factors that may influence workplace stressors and environments. Future studies could benefit from examining how the impact of AI adoption on job stress and burnout varies across different industries.

Seventh, we did not include job satisfaction as a control variable. This variable could influence employees' stress and burnout levels, potentially affecting the relationship between AI adoption and these outcomes. Future research could incorporate job satisfaction measures to more precisely isolate the specific effects of AI adoption.

Lastly, our study did not account for organizational culture, which can significantly impact employee stress and burnout, as the influence of AI adoption on employee outcomes may vary depending on the organizational context. Future studies could explore how different organizational cultures moderate the relationships examined in our research.

As this paper emphasizes the mediating function of work stress and the moderating function of self-efficacy in AI learning, we conclude that AI adoption positively affects employee well-being. Nevertheless, additional research is needed to improve the current understanding of the complex relationships between AI adoption, job stress, and burnout in various settings. Such research should employ multi-method approaches and take into account a wide array of individual and organizational characteristics. Future research can fill these gaps left by the present study and expand upon the current findings to create evidence-based methods to support employees' health and resilience in the face of rapid technology advancements.

Conclusion

The rapid advancement and widespread deployment of AI technologies across enterprises have changed work dynamics and employee experiences. It is critical to investigate the effects of this technological change on workers' mental health as AI keeps changing how people perform their jobs. To elucidate the processes and boundary conditions impacting employee outcomes in the AI era, the current paper investigated the complex interplay between different variables.

This study revealed complicated paths by which the adoption of AI affects employee burnout using a thorough three-wave time-lagged design. The results challenge the notion that the use of AI is directly related to burnout, instead highlighting the critical mediation function of job stress. Adapting to new tools, confusion about job tasks, and a larger workload are some of the additional job demands that employees may face as firms incorporate AI technologies. AI pressures can drain workers' emotional and mental reserves, leading to increased work stress and burnout.

In addition, the study shows that self-efficacy in AI learning significantly moderates the association between AI adoption and job stress. An employee's stress level caused by the negative effects of AI adoption will be lessened if they have faith in their ability to become an expert in AI. This discovery highlights the significance of empowering employees through focused training and development programs so they can thrive in the face of technological change.

Organizations undergoing AI transformation can greatly benefit from the present study's findings. Most importantly, organizations must understand that there is more to successful AI

adoption than simply implementing technology. Human factors, especially the mental health and resiliency of workers interacting with AI systems, must also be carefully considered. Organizations may create more positive and productive work environments for their employees by anticipating and mitigating any harmful impacts of AI adoption on stress and burnout on the job.

In addition, this study highlights the need for self-efficacy in AI learning to mitigate the harm that AI adoption could do to employees' well-being. Companies should invest in comprehensive training and development programs that teach workers the technical skills they require and help them feel confident in their ability to master AI. Organizations can foster a workforce that can manage AI adoption by providing workers with the knowledge and skills they need to make good use of AI technologies.

This study also contributes to the growing literature on the mental health effects of AI at work. This study integrated the JD-R model with SCT to better comprehend the complex associations between AI adoption, job stress, self-efficacy in AI learning, and burnout. This study lays the groundwork for future studies to examine other factors that may impact these relationships in different cultural and organizational contexts. It also highlights the importance of the mediating and moderating mechanisms that impact employee experiences concerning AI adoption.

Data availability

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

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Author contributions

Byung-Jik Kim contributed by writing the original draft of the manuscript and participating in the conceptualization, data collection, formal analysis, and methodology. Julak Lee contributed to the conceptualization, analysis, revision, and editing of the manuscript. All authors contributed to the writing of the final manuscript and have read and agreed to the published version of the manuscript. All members of this research team contributed to the management or administration of this paper.

Competing interests

The authors declare no competing interests.

Ethical approval

The survey conducted in this study adhered to the standards outlined in the Declaration of Helsinki. The Yonsei University Institutional Review Board granted ethical approval. Approval number: 202208-HR-2975-01. Date of approval: 15.08.2022. Scope of approval: All research variables in this study.

Informed consent

Informed consent was obtained. Every participant was provided with information about the objective and extent of this study, as well as the intended utilization of the data. The respondents willingly and freely participated in the study. Their identities were kept confidential, and their involvement was optional. Prior to participating in the survey, all subjects included in the study provided informed consent. Informed consent was obtained from March 2022 to April 2022 through the website of the research company (Macromil Embrain). The scope of the consent covered participation, data use, and consent to publish. Online explanatory statement and documents related to exemption from written consent. Since the explanatory statement requires consent three times, it was submitted on the first, second, and third questionnaires. By default, written consent was waived. The reason for this is as follows. This survey was conducted through Macromil Embrain, a research company that has the largest panel in Korea (25 years of experience in the industry). Individuals belonging to the panel of Macromil Embrain registered in the company's survey response system and agreed to provide their information and survey content. Then, they logged in to the system and responded to the survey. At this time, the research company announced the contents of the researcher's survey, and panels interested in the survey participated in the survey. Alternatively, the research company asked those who were qualified to participate in the survey (e.g., office workers at a domestic company) via e-mail or text message about their intention to participate in the survey. This process was conducted entirely online, and it was practically impossible to obtain the consent of the research subjects because the researcher did not know which panel would respond to the questionnaire. Sufficient voluntary participation in research was ensured, and explanations regarding the guarantee of withdrawal and suspension of participation were supervised by the aforementioned research company. A research company manages this company's website by asking for consent when an individual signs up and registers. When a person signs up for this

company's service as a panel, these matters are explained in detail, and consent is obtained. Only those who gave their consent participated in the survey. The condition for selecting study subjects was that they must have been adult employees working for domestic companies. If participants were adult employees working for a domestic company, there were no special conditions such as regular or non-regular workers. People excluded from the study were those who were not currently working or who did not have the intellectual ability to understand and respond appropriately to the questionnaire. Also, people with limited ability to give consent for research or those who were vulnerable were not included as research subjects. Only those panels who had voluntarily registered to participate in the survey with the research company (Macromil Embrain) took part in the survey. In particular, when issuing a recruitment notice, the general subject and risks of the study were noted, and personal privacy was ensured during recruitment. Steps were taken to ensure the protection and confidentiality of participants. We did not include vulnerable research subjects. Vulnerability could be judged voluntarily by survey respondents. In addition, only those who met the research company's criteria (mentioned above) could participate in the survey. The process and contents of the second and third surveys were the same as in the first survey.

Additional information

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