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Insights from the Job Demands–Resources Model: AI's dual impact on employees' work and life well-being

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ABSTRACT

Artificial intelligence (AI) has rapidly integrated into organizational workflows, sparking two debates: proponents argue that it increases productivity and decreases workloads, whereas opponents warn that it induces technostress (e.g., job replacement) and decreases employees' well-being. However, AI adoption by employees remains understudied, requiring both theoretical and empirical investigation to assess its positive and negative effects. This study employs the job demands–resources (JD–R) model as a guiding framework to examine the impact of AI demands (i.e., technostress) and resources (i.e., efficacy and generative AI) on employees' work and life domains (i.e., productivity, job satisfaction, and work–family conflict), with engagement and exhaustion as mediating factors. Data gathering through a three-wave survey involved 600 gender-balanced participants working with AI across diverse industries. Bayesian SEM results indicate that both AI efficacy and generative AI positively impact productivity, with AI efficacy also enhancing engagement and job satisfaction. In contrast, AI technostress increases exhaustion, exacerbates work–family conflict, and lowers job satisfaction, even though it may still contribute to productivity. These findings highlight the dual impact of AI on employees: AI technostress impairs well-being, while AI efficacy enhances it. Notably, generative AI mitigates the negative effects of technostress, a benefit not observed for AI efficacy as measured in this study. Overall, this study provides an empirical basis for understanding the resources and demands associated with AI adoption and its impact on employees' psychological processes, influencing both their work and life domains and leading to diverse outcomes.

1. Introduction

Artificial intelligence (AI) is transforming work and learning, becoming a crucial aspect of the future of labor and significantly impacting human life (Huang & Rust, 2018; Makarius et al., 2020). AI simulates human cognition and can automate mundane tasks and generate content (Siemens et al., 2022). Examples include using affective responses in recruitment processes (Köchling et al., 2023); integrating AI chatbots to improve the customer experience (Chen et al., 2021; Sidaoui et al., 2020); employing AI of Things (AIoT) to support various applications such as transportation, health care, grids, and home (Zhang & Tao, 2020); and facilitating predictive analytics for stock trading and fraud detection systems in finance (Cao, 2022). Furthermore, the introduction of ChatGPT in late 2022 accelerated the adoption of AI in workplaces, particularly in the realm of 'generative AI', which rapidly generates content and is a cutting-edge technology in business. These diverse AI technologies not only optimize task processes and precision but also create significant economies of scale (Wang et al., 2024).

Indeed, AI represents an advanced form of information and communication technology (ICT), and its goal is to complement, strengthen, or complete tasks traditionally performed by humans (Makridakis, 2017), which elicits both optimism and concern. Optimistic scholars argue that AI increases work efficiency, decreases monotonous routine tasks, and improves work quality (Klenert et al., 2023; McGuinness et al., 2023), potentially increasing job opportunities for women and inexperienced workers (Brynjolfsson et al., 2023; Shen & Zhang, 2024) and addressing the challenges posed by declining birth rates and labor shortages in some regions (Yeh, 2023). Cautious scholars warn of AI-induced 'technostress' (Wang, 2023), especially through employees fearing job displacement (Huang & Rust, 2018; Li et al., 2019; Morgan, 2019), facing the challenge of adapting to evolving

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technology and transitioning to new roles requiring AI-related skills (Wang, 2023), which can reduce engagement, jeopardize psychological well-being (Brougham & Haar, 2018; McClure, 2018), and increase turnover intentions (Li et al., 2019). In addition to scholars' views, we administered a questionnaire to understand employees' opinions of AI (see Appendix A). The majority of employees strongly endorsed the use of AI for both personal and company development (77.2 % and 79.7 %, respectively) and agreed that AI supports their job (63.6 %), whereas they also expressed concerns about AI potentially leading to displacement (62.8 %). It is clear that the integration of AI technology stirs both a sense of urgency and concern among employees, carrying the potential for diverse effects.

Hence, understanding how the light and shadow aspects of AI truly impact employees' work and lives has become an important research topic. Scholars have noted that integrating AI in the workplace presents a promising avenue for new studies. However, most studies on AI and workers have primarily focused on human—machine collaborations (e.g., Makarius et al., 2020; Zirar et al., 2023), while paying less attention to the broader implications of AI adoption on employees' overall work—life experiences. Many of these studies are still in the theoretical development phase, offering limited empirical research. For example, Makarius et al. (2020) theorized AI–human collaboration through sociotechnical capital, and Zirar et al. (2023) highlighted AI–worker dynamics, addressing perceived threats, enhanced capabilities, coexistence, and training needs. Moreover, several AI paradoxes have been identified across different work and life domains (Charlwood & Guenole, 2022; Raisch & Krakowski, 2021). For instance, Bäck et al. (2022) suggested that AI adoption does not always increase productivity among early adopters because of technological immaturity. Similarly, Bhargava et al. (2021) conducted interviews with AI users across various industries and countries and revealed that AI can exacerbate the job satisfaction dilemma. This highlights the necessity of developing both theoretical and empirical research to address the impact of AI on employees' work and lives comprehensively.

To answer this research question, we utilize the job demands–resources model (JD–R model; Bakker & Demerouti, 2017; Bakker et al., 2023; Demerouti et al., 2001) as a guiding framework to identify AI-related strains and supports at work and examine their relationships with employees' work and life domains. The JD–R model is a work design theory that integrates various perspectives on job stress and motivation (Bakker & Demerouti, 2017). This theoretical framework explains how the work environment influences the physical and mental health of employees through two crucial elements: job demands and resources. We categorize the demands represented by 'technostress' and the resources associated with AI features, specifically 'efficacy' and 'generative AI.' AI efficacy refers to the perceived usefulness and reliability of AI systems, while the generative AI is compared with nongenerative AI. By utilizing the tenets of the JD–R model, which posits that the physical and mental energy consumed by demands can lead to exhaustion while resources can stimulate engagement in work (Bakker & Demerouti, 2017; Bakker et al., 2023), we examine its impact on employees' productivity, job satisfaction, and work–family conflict. This framework provides both theoretical and empirical support to explain the positive and negative impacts of AI adoption on employees' work and life domains.

This study advances the literature in multiple ways. First, it adopts the JD–R model to provide a theoretical framework that explains the resources and demands associated with AI's impact on employees' work and well–being. This model not only deepens our understanding of how AI adoption affects work—life dynamics but also explores potential psychological processes by examining the mediating roles of engagement and exhaustion. Second, this study introduces generative AI as a variable compared with nongenerative AI. Generative AI systems create new content by learning patterns from data and can potentially transform any domain that values creativity and innovation (Marr, 2023). In contrast, nongenerative AI systems (e.g., traditional AI or discriminative AI) are designed to perform specific tasks intelligently by following rules and predefined strategies (Marr, 2023). These empirical findings are particularly significant given the increasing adoption of generative AI in workplaces. Third, this study not only investigates the impact of AI paradoxes on productivity and job satisfaction but also uniquely explores the relationship between AI adoption and work–family conflict, contributing to a broader understanding of work and life well–being.

In the research design and analysis, the study employed a three-wave questionnaire using a temporal approach to collect data, aiming to identify the direction of influence among variables (Collins, 2006). Data were gathered from employees across various industries and companies that have adopted AI technology, enhancing the generalizability of the findings. Bayesian structural equation modeling (BSEM) was used for analysis, as it provides a more flexible and comprehensive framework for estimating complex models with parameter uncertainty (Stromeyer et al., 2015; Van de Schoot et al., 2017), ultimately yielding more accurate results.

2. Theoretical backgrounds

2.1. JD–R Model at work

The JD–R model (Bakker & Demerouti, 2017; Bakker et al., 2023; Demerouti et al., 2001) explains how the work environment impacts employees' physical and mental health through job demands and job resources. Job demands are the continuous physiological, cognitive, or emotional efforts required in the workplace and can lead to health issues and fatigue. Job resources are factors that promote goal achievement, personal growth, and development, providing positive motivation. Scholze and Hecker (2024) indicated that the JD–R model provides a useful theoretical framework for understanding changes in job demands and resources resulting from digitization, capturing both its positive (bright side) and negative (dark side) effects and allowing for a structured classification of these impacts.

According to the JD–R model, the physical and mental energy expended due to job demands can result in 'exhaustion' and self-undermining, whereas job resources enhance employees' 'engagement' and proactive behavior (Bakker & Demerouti, 2017; Bakker et al., 2023). Schaufeli et al. (2002) defined exhaustion as psychological strain characterized by feelings of depletion and the overuse of emotional and physical resources. Research shows that exhaustion undermines employees' performance, commitment, and organizational behavior due to insufficient resources for positive engagement (Bakker et al., 2023). In contrast, Schaufeli et al. (2002) described work engagement as a state of vigor, dedication, and absorption, combining satisfaction with heightened activation. Actively engaged employees experience purpose, excitement, challenge, and a strong attachment to their tasks (Bakker et al., 2023). In other words, the JD–R model proposes two distinct processes (Bakker et al., 2023) arising from job demands and resources: the health impairment process, where job demands deplete employees' physical and mental resources, leading to strain, exhaustion, and potential health issues; and the motivational process, where job resources fulfill employees' psychological needs, enhancing engagement and fostering creativity and performance.

Below, we provide a brief overview of AI, focusing on its demand aspects (i.e., AI technostress) and resource aspects (i.e., AI efficacy and generative AI).

2.2. Artificial Intelligence (AI)

AI comprises computer systems that mimic human cognitive processes (Siemens et al., 2022) and behavioral responses while autonomously interpreting data for self-correction and updates (Haenlein & Kaplan, 2019; Siemens et al., 2022). AI technology, heralded as the Fourth Industrial Revolution (Morgan, 2019; Syam & Sharma, 2018) and marking the onset of the Algorithmic Age (Danaher et al., 2017), performs tasks that typically require human intelligence and encompasses various aspects, such as machine learning, natural language processing, visual recognition, and decision support systems. Unlike previous technological advancements that have focused primarily on routine manual tasks, AI technology involves more complex and cognitive functions (Syam & Sharma, 2018). The capabilities of AI include the physical automation of manipulating and moving objects, recognition, problem-solving, and innovation (Benbya et al., 2020), allowing it to make decisions, learn, and interact autonomously (Haenlein & Kaplan, 2019).

2.2.1. Technostress from AI

Technostress from AI can serve as a job demand that influences employees' work. Technostress is the adverse psychological impact stemming from the introduction of new technologies (Ayyagari et al., 2011; Tarafdar et al., 2007). Technostress arises from individuals' efforts to cope with evolving technologies and their changing cognitive and social demands (Tarafdar et al., 2007). The five factors of technostress are as follows: 't-overload' pushes users to work faster and longer; 't-invasion' blurs the boundary between work and personal life; 't-complexity' arises from technologies being too complicated; 't-insecurity' stems from the fear of job loss to technology or more skilled individuals; and 't-uncertainty' results from constant technological changes, necessitating ongoing education.

Wang (2023) highlighted that the potential for job displacement (i.e., t-insecurity) due to AI, the challenge of unfamiliar AI technology (i.e., t-complexity), and the increased workload required to learn AI systems (i.e., t-overload and t-uncertainty) can increase technostress levels and decrease self-efficacy among employees. A study by Wei and Li (2022) on the use of AI in the Chinese manufacturing industry revealed that the use of AI technology was significantly positively correlated with overtime (i.e., t-overload and t-invasion), indicating that AI technology did not reduce the working hours of manufacturing workers but rather increased them. This technostress places demands on employees, requiring them to expend energy to overcome it, which may have adverse effects, such as a lack of consensus on human-AI collaboration (Brock & von Wangenheim, 2019; Seeber et al., 2020). Therefore, the technostress associated with AI is likely to manifest as demands and urgency on employees, affecting their work and life.

2.2.2. Efficacy of AI

AI efficacy is a resource that supports employees' work, similar to the usability feature of ICT mentioned by Ayyagari et al. (2011). Two dimensions are of concern: usefulness, which is AI's ability to effectively improve work productivity, and reliability, which pertains to the dependability of AI technology performance and its relation to user trust in the technology.

Usefulness is the most influential factor affecting users' willingness to adopt technology, as it can help individuals overcome their fear of technology products and reluctance to learn (Liu et al., 2015). AI provides employees with an alternative way to interact with technology that requires minimal skills and results in the perception of technology as easy to use (Guzman, 2020). Chattaraman et al. (2019) also indicate that AI services typically increase the ease of using technology because of the advanced nature of these systems. Furthermore, reliability is a key factor in employee–AI collaboration (Kong et al., 2023; Makarius et al., 2020), and it is closely connected to trustworthy AI services (Glikson & Woolley, 2020; Kong et al., 2023). The reliability of AI involves various aspects of human–AI collaboration, which may include other attributes of AI services, such as the extent of social interaction and perceived intelligence, as well as the form and sophistication of the system (Glikson & Woolley, 2020; Makarius et al., 2020). The usefulness and reliability of AI enable employees to efficiently complete tasks by allowing them to search for information according to their preferences (Guzman, 2020). Thus, 'usefulness' and 'reliability' can serve as factors of AI efficacy, boosting individuals' adoption of and trust in technology and acting as resources to enhance employees' work and life domains.

2.2.3. Generative AI

In addition, the new types of AI can also be considered resources for functional improvement instead of merely user-perceived improvements (i.e., efficacy). Generative AI is a new form of AI, in contrast to nongenerative AI (e.g., traditional or discriminative AI). Generative AI is trained on large amounts of existing data to generate new content and excels in innovation and handling uncertainty (Marr, 2023). In contrast, nongenerative AI systems rely on human input to define the parameters of their learning algorithms and provide the necessary training data to ensure accuracy, making them effective at solving specific tasks (Marr, 2023). Traditional AI has existed for decades and is integrated into many widely used technologies, such as search engines, voice assistants, and chatbots, all excelling in specific functions. According to Makarius et al. (2020), in the context of AI integration at work, generative AI demonstrates greater innovation and can either operate independently or complement employees. In interactions with generative AI, employees often assume the roles of checkers and collaborators. Conversely, with nongenerative AI, employees tend to take on more controlling and directive roles (Makarius et al., 2020). Although generative and nongenerative AI have distinct functionalities, they are not mutually exclusive (Marr, 2023). Therefore, we regard the generative AI as a powerful job resource that is potentially more impactful than the early adoption of nongenerative AI and capable of improving employees' work and life domains.

2.3. Work and life outcomes

Productivity is intricately tied to the concept of efficiency, which is associated with technical proficiency and optimal resource allocation practices (Rogers, 1998). It is also related to various costs associated with production, including time, innovation, satisfaction, and managerial control (Hung et al., 2015; Tarafdar et al., 2007). Grosskopf (1993) suggested that technological advancements play a pivotal role in driving productivity growth, as they lead to improvements in effectiveness and shifts in the production frontier.

Job satisfaction, the general extent to which employees are satisfied with their work (Agho et al., 1992), reflects the subjective well-being experienced by workers on the basis of their personal assessment of fulfillment derived from their work (Schwabe & Castellacci, 2020). Employees' job satisfaction significantly impacts their overall subjective well-being (Joo & Lee, 2017), and dissatisfaction can lead to reduced motivation, increased turnover rates, and diminished innovation in the economy (Schwabe & Castellacci, 2020).

Work—family conflict occurs when individuals manage responsibilities and demands in both the work and family spheres (Carlson et al., 2000; Van Daalen et al., 2006), resulting in insufficient time and commitment to one domain over the other. While work–family conflict encompasses both work-to-family and family-to-work conflict, this study specifically addresses work-to-family conflict. This focus is due to the limited influence of work demands and resources on family-to-work conflict (e.g., Chuang et al., 2024; Van Daalen et al., 2006).

2.4. Prior related research

This study utilized the Web of Science database to search for articles via the keywords "Artificial Intelligence" and "job demands–resources model," leading to the discovery of 3 relevant papers[1] (Yu et al., 2025; Wu et al., 2024; Zuo et al., 2024). Wu et al. (2024) focused on Chinese employees working with AI and reported that job insecurity increases anxiety, which in turn negatively impacts creativity, informal learning, well-being, and psychological health. However, workplace mindfulness

[1] We conducted the search in October 2024

was found to reduce these negative effects. Zuo et al. (2024) studied Chinese teachers and discovered that the perceived usefulness of technology significantly enhances online teaching engagement and the intention to continue, with institutional support being crucial for maintaining their online teaching efforts. Yu et al. (2025)examined how algorithmic management influences worker behavior, revealing that high levels of algorithmic control reduce service quality and referral behaviors, but a heavy workload can act as a challenge demand, helping to offset the adverse effects of algorithmic management. These three articles suggest that adopting the JD–R model is appropriate for explaining the complex effects of AI adoption. However, these studies may emphasize either the negative aspects of AI, such as technostress (e.g., Wu et al., 2024), or its positive aspects, such as usefulness (Zuo et al., 2024), research that integrates both positive and negative perspectives is still needed.Additionally, several studies with objective measurements of AI and output (e.g., Brynjolfsson et al., 2023; Peng et al., 2023; Noy & Zhang, 2023) published after 2023 revealed the advantages of AI adoption in productivity. However, Bäck et al. (2022) indicated that AI adoption does not always increase productivity due to technological immaturity (i.e., t-complexity) in its early stages. Moreover, some studies suggest that AI adoption may improve job satisfaction (e.g., Braganza et al., 2022; Sony & Naik, 2020) owing to its benefits in automation and collaboration, while Bhargava et al. (2021) also highlighted that technostress from AI may lead to lower job satisfaction. These paradoxes in productivity and job satisfaction reveal the need for a comprehensive framework to explain these conflicting results. Furthermore, we searched using the keywords 'Artificial Intelligence' combined with 'work–family conflict,' 'work–life well-being,' and 'work–life balance.' While we found limited qualitative research, such as studies on female medical workers (Capelli et al., 2023) and financial engineers(Gao & Zamanpour, 2024) , empirical studies on this topic remain scarce. Therefore, this study not only aims to investigate the paradoxes of productivity and job satisfaction through the lens of the JD–R model, but is also the first empirical study to explore the relationship between AI adoption and work–family conflict, providing a deeper understanding of this issue.

3. Research model and hypotheses

Our research investigates the dual impact of AI on employees' work and life well-being, framed by the JD–R model. Fig. 1 illustrates the relationships under investigation in the present study.

3.1. Impacts of AI efficacy and the generative AI

According to the JD–R model, job resources can mitigate the impact of job demands (Bakker et al., 2003); thus, the efficacy of AI and the generative AI may alleviate technostress. First, employee-perceived AI efficacy plays a crucial role in influencing technostress levels (Xia, 2023). AI, designed to mimic human cognition and actions through intelligent process automation (Mandvikar & Achanta, 2023), can streamline workflows by reducing the time spent on repetitive tasks and improving output quality and consistency. Consequently, high AI efficacy alleviates cognitive burdens, reduces time pressure, and minimizes errors in the workplace (Park et al., 2021; Rožman et al., 2023), thereby lowering technostress. In contrast, when employees perceive AI tools as ineffective or unreliable, their technostress is likely to increase (Bondanini et al., 2020).

Second, generative AI offers notable advantages over nongenerative AI in mitigating technostress. By enhancing functionality for idea generation and automating content creation, generative AI allows users to easily produce text, images, or multimedia using simple instructions (Fui-Hoon Nah et al., 2023). This user-friendly design eliminates the need for mastering complex operations, thereby reducing the stress often associated with adapting to new technologies. Moreover, generative AI delivers personalized learning opportunities through tailored training and support, enabling employees to acquire AI-related skills more effectively (Morandini et al., 2023; Yan et al.,2024). This personalized approach addresses concerns about job security and skill development (Xia, 2023), further underscoring its potential to alleviate technostress. Thus, we hypothesize the following:

Hypothesis 1. (a) The efficacy of AI and (b) generative AI adoption are negatively associated with technostress from AI at work.

Human–AI collaboration relies on the usefulness and reliability of AI. This collaboration facilitates employee improvement, helps organizations become more competitive (Chowdhury et al., 2022) and becomes a crucial work behavior that increases employees' job well-being and productivity (Kong et al., 2023). Empirical studies indicate that access to AI assistance can significantly increase productivity. For example, AI-enabled systems have been shown to improve agent productivity by 14 %, as measured by the number of customer issues resolved per hour (Brynjolfsson et al., 2023). Additionally, AI represents a form of 'tacit knowledge' fundamental to numerous tasks, simplifying work processes and improving employee satisfaction (Hou, 2012).

In addition, AI system automation has also been shown to enhance

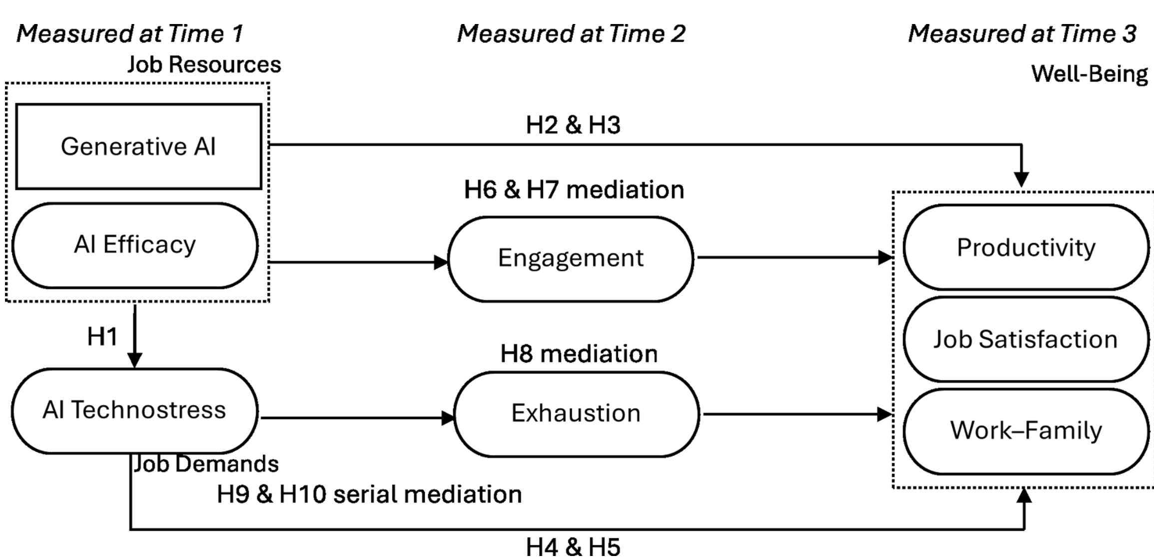

Fig. 1. Research Framework. *Note.* For the generative AI, 1 =yes, 0 =no; the boxes represent observed variables, and the other variables are latent variables.

job engagement and satisfaction, as evidenced by studies involving workers using intelligent systems to support their tasks (Braganza et al., 2022). These benefits extend beyond productivity, promoting employee well-being and enabling collaboration with cutting-edge technologies (Sony & Naik, 2020). Furthermore, AI's ability to provide precise results reduces operational errors, saving employees time and energy while allowing them to better balance their work and family responsibilities (Brynjolfsson et al., 2023; Paschen et al., 2020).

Hypothesis 2. The efficacy of AI at work is positively associated with (a) productivity and (b) job satisfaction but (c) negatively associated with work–family conflict.

Generative AI offers distinct advantages over nongenerative AI in enhancing productivity and reducing stress. Noy and Zhang (2023) found that participants using generative AI tools like ChatGPT could complete professional writing tasks more efficiently than those without access to these technologies. Similarly, Peng et al. (2023) demonstrated that software engineers using AI tools such as Copilot completed coding tasks twice as quickly as their peers without generative AI support.

Similar to widely used AI, generative AI boosts productivity by freeing up time and energy, allowing employees to focus on more meaningful and rewarding activities, enhancing job satisfaction (Chiong & Xie, 2024). Additionally, generative AI reduces employee involvement in repetitive tasks, helping alleviate negative emotions and promoting a healthier work–life balance (Dwivedi et al., 2021).

Hypothesis 3. Generative AI adoption at work is positively associated with (a) productivity and (b) job satisfaction but (c) negatively associated with work–family conflict.

3.2. Impact of AI technostress

On the other hand, employees might experience technostress when using AI at work because of associated job demands. A meta-analysis conducted by Gerdiken et al. (2021), which included 96 empirical studies, revealed negative relationships between technostress and employees' job performance, creativity, and job satisfaction, whereas technostress exhibited significant positive relationships with employees' work-to-family conflict and turnover intentions. Tarafdar et al. (2007) discovered that technostress resulting from the use of ICTs is inversely correlated with productivity; lower levels of technostress can result in greater productivity. Alam (2016) investigated technostress—specifically, complexity, uncertainty, and overload—in the aviation industry and reported that technostress had a stronger negative effect on crew productivity when employees experienced greater role overload and equity sensitivity. Other scholars, such as Li and Wang (2021), Tiwari (2021), and Pirkkalainen et al. (2019), have also reported a negative relationship between technostress and productivity. Additionally, the integration of AI into the workplace may lead to concerns about potential job displacement, resulting in mental stress, anxiety, fear, and insecurity about one's current job, which negatively impacts job satisfaction (Califf et al., 2020; Koo et al., 2021; Schwabe & Castellacci, 2020). Califf et al. (2020) suggested that numerous challenges and obstacles associated with technostress can elicit both beneficial and unfavorable psychological reactions, which in turn affect job satisfaction, consequently impacting turnover intention. Furthermore, the cloud-based control of AI services enables work from any location at any time (Robertson et al., 2021), blurring the distinction between work and personal life. This often leads to increased workloads and heightened stress (i.e., t-invasion). Gadeyne et al. (2018) reported that using a PC or laptop for work outside work hours is positively associated with work–family conflict. T-complexity and t-insecurity also consume employees' energy and increase their effort, limiting their ability to balance work and life. Therefore, we hypothesize the following:

Hypothesis 4. Technostress from AI adoption at work is negatively associated with (a) productivity and (b) job satisfaction but (c) positively associated with work–family conflict.

However, not all technostress contributes to adverse work outcomes (Gerdiken et al., 2021; Yuan et al., 2023). Some scholars have reported that t-overload increases productivity and improves performance (e.g., Hung et al., 2015; Zhao et al., 2020) and job satisfaction (Aktan & Toraman, 2022). Hung et al. (2015) reported that t-overload increases productivity for work-related mobile phone users, whereas communication overload decreases it. Additionally, Zhao et al. (2020) indicated that using ICTs induces t-overload and t-uncertainty, which benefit productivity, as employees perceive these challenges as opportunities to meet both personal and organizational requirements. Moreover, a meta-analysis conducted by Yuan et al. (2023) indicated that t-uncertainty does not impact performance, and Gerdiken et al. (2021) also indicated that t-uncertainty challenges technostress owing to its positive association with performance. Aktan and Toraman (2022) conducted a study involving 525 teachers who experienced intensive use of technology in distance education during the COVID-19 pandemic and reported a positive association between t-uncertainty and job satisfaction. Yuan et al. (2023) highlighted that the consequences of technostress are inconsistent and fragmented, with variations in its impact on job performance influenced by the sample's gender, education, and employment. The above discussion reveals the complex results of technostress, as different dimensions may yield varying outcomes for investigated variables. Although we focus on aggregated technostress rather than individual stressors, ignoring these possible findings might be misleading. Therefore, we propose the following conflicting hypotheses:

Hypothesis 5. Technostress from AI adoption at work is not negatively associated with (a) productivity or (b) job satisfaction; instead, the association is either positive or nonexistent.

3.3. Mediating roles of engagement and exhaustion

According to the JD–R model, job resources and demands instigate two different processes (Bakker & Demerouti, 2017; Bakker et al., 2023): the former is associated with the motivational process, and the latter is associated with the health impairment process. In the motivational process, job resources satisfy basic psychological needs and foster employees' engagement. Research in this field has consistently demonstrated a positive correlation between various types of job resources and engagement (e.g., Lesener et al., 2020; Mazzetti et al., 2023). Several studies have indicated that positive AI attributes are positively associated with employee engagement, which mediates the relationship between AI attributes and performance (Prentice et al., 2023; Wang, Chen, et al., 2023). Thus, AI efficacy and generative AI should serve as job resources, enhancing employees' engagement and subsequent work and life outcomes.

Hypothesis 6. AI efficacy is positively related to engagement, and engagement mediates the relationships between efficacy and (a) productivity, (b) job satisfaction and (c) work—family conflict.

Hypothesis 7. Generative AI adoption at work is positively related to engagement, and engagement mediates the relationships between Generative AI and (a) productivity, (b) job satisfaction and (c) work—family conflict.

In the health impairment process, job demands can considerably increase exhaustion by depleting employees' physical, emotional, and cognitive resources, which diminishes their performance (Bakker & Demerouti, 2017; Bakker et al., 2023). AI awareness stress, such as job insecurity, can induce negative effects for employees, with exhaustion mediating the relationship between AI awareness and outcomes such as depression (Xu et al., 2023) and withdrawal (Teng et al., 2023). Technostress from AI may have a similar tendency, as demands arouse a psychological process that results in more exhaustion. Gerdiken et al. (2021), through a meta-analysis, reported that technostress is positively related to exhaustion. Thus, technostress from AI should serve as a job demand, increasing employees' exhaustion and affecting their work and life outcomes.

Hypothesis 8. Technostress from AI is positively related to exhaustion, and exhaustion mediates the relationships between technostress and (a) productivity, (b) job satisfaction and (c) work–family conflict.

3.3.1. Serial mediation

Following the aforementioned inference, the AI efficacy/generative AI, technostress, exhaustion, and outcome variables (including productivity, job satisfaction, and work–family conflict) may exhibit serial mediation effects. Specifically, AI efficacy/generative AI could decrease the impacts of technostress and exhaustion on outcome variables. Thus, we propose serial mediation effects between AI efficacy/generative AI, technostress, exhaustion, and outcome variables.

Hypothesis 9. The efficacy of AI is associated with (a) productivity, (b) job satisfaction, and (c) work—family conflict via the chain mediation of technostress and exhaustion.

Hypothesis 10. Generative AI adoption is associated with (a) productivity, (b) job satisfaction, and (c) work—family conflict via the chain mediation of technostress and exhaustion.

4. Materials and methods

4.1. Participants and procedure

This study was a component of a broader research framework that was implemented from October to December 2023 and received approval from the Research Ethics Committee of the National Taiwan Normal University (REC Number: 202310HS020; "A Survey of the Impact of Artificial Intelligence"). Under our research hypotheses, we enlisted the services of a market research firm to collect data, necessitating a sample of 600 employees with an equal distribution of 50 % male and 50 % female representation. The sample pool included publicly listed companies in Taiwan that had adopted AI in their work operations.

The survey consisted of three waves with intervals over a week. The participants received an exclusive link through mobile messages and emails to access the questionnaire. In the initial survey (Time 1), the participants received an informed consent form and answered demographic questions and a question about AI adoption at work (see Appendix A), a question about AI adoption duration at work, an open-ended question about specific AI adoption at work, and a question about the efficacy of AI and technostress from AI adoption. The second survey (Time 2) was distributed one week after the first survey and focused on measuring employees' engagement and exhaustion. The last survey (Time 3) was administered one week after the second survey, and employees' productivity, job satisfaction, and work–family conflict were assessed.

According to the market research firm's report, 2238 employees from 1756 companies were contacted. Of these, 889 (39.7 %) refused to participate, 573 (25.6 %) did not meet the criteria, and 176 (7.8 %) did not complete the survey. Ultimately, 600 valid responses were collected from 365 companies, resulting in a 26.8 % successful response rate from real contacts and achieving the target with a balanced gender distribution. The average age of the 600 participants was 39.21 years (SD = 8.83), and the average organizational tenure was 9.33 years (SD = 7.96). For additional demographic details, see Table 1.

Table 1
Demographic Descriptions.

		N = 600	
		Numbers	Percentage
Gender	Male	300	50.0 %
	Female	300	50.0 %
Age	21–30 years old	102	17.0 %
	31–40 years old	256	42.7 %
	41–50 years old	175	29.1 %
	51 years old and above	67	11.2 %
Education	High school or below	9	1.5 %
	Bachelor's degree	404	67.3 %
	Master's degree	184	30.7 %
	Doctoral degree	3	0.5 %
Marriage	Single	274	45.7 %
	Married	326	54.3 %
Have Children	Yes	328	54.7 %
	No	272	45.3 %
Job Tenure	Below 2 years	104	17.3 %
	2–5 years	130	21.7 %
	5–10 years	148	24.7 %
	10–15 years	90	15.0 %
	15–20 years	66	11.0 %
	20 years and above	62	10.3 %
Supervisor Position	Yes	179	29.8 %
	No	412	70.2 %
Industry	Finance/Insurance/Securities	139	23.2 %
	Electronics/Technology-related	192	32.0 %
	Traditional Industries	182	30.3 %
	Others	87	14.5 %
Position	HR/Finance/Administration	131	21.8 %
	R&D/Technology	178	29.7 %
	Marketing/Sales	126	21.0 %
	Manufacturing/Quality Control	47	7.8 %
	Others	118	19.7 %
AI Adoption Duration	3 months and below	113	18.8 %
	3 months to 6 months	111	18.5 %
	6 months to 1 year	217	36.2 %
	1 year to 2 years	77	12.8 %
	More than 2 years	82	17.3 %

4.2. Measurements

In addition to the open-ended questions, the measured items underwent a translation and back-translation process, which was managed by a professional translation company. Before formally conducting the survey, research team members collectively reviewed and confirmed the accuracy of the translated content. Responses were recorded on a 7-point agreement Likert scale (*1 =disagreed, 7 =agreed*), unless otherwise specified.

4.2.1. Main measurement

Generative AI Adoption at Work (1=Yes, 0=No; Time 1): Whether generative AI was used in the workplace was determined by the research team on the basis of responses to an open-ended question about "the specific AI applications used at work". Owing to the open-ended nature of the questions, the respondents provided information, including software names or job execution details. We categorized respondents' use of AI at work into generative AI or nongenerative AI on the basis of these answers. Keywords related to generative AI software (such as ChatGPT, Bard AI, Copilot, Gamma, Yolo, Midjourney, and Notion AI) or job execution content involving AI drawing, automatic text generation, code generation, checking, and debugging were coded as 1. However, if respondents mentioned only general AI assistants (e.g., intelligent customer service), data inquiries, a smart housekeeper, an inspection machine, smart glasses, etc., it was identified as nongenerative AI and coded as 0. Approximately 45.5 % of the 273 responses were identified as relevant to generative AI (yes=1), whereas approximately 54.5 % of the remaining responses were classified as nongenerative AI (no=0).

AI Efficacy (Time 1): According to Ayyagari et al.'s (2011) usability features of technology, we revised and measured *usefulness* and *reliability*. ***Usefulness*** included four items, including 'Using AI allows me to accomplish tasks more quickly.' Cronbach's α was.91. ***Reliability*** included three items, including 'The functionalities provided by AI are reliable.' Cronbach's α was.89. The Cronbach's α of overall efficacy was.89.

AI Technostress (Time 1): Tarafdar et al.'s (2007) five components of ICT-related technostress were revised for use. The participants received instructions such as 'Regarding the AI technology used in your work….' ***(1) T-overload*** included five items, such as 'I am forced by this technology to do more work than I can handle.' Cronbach's α was.89. ***(2) T-invasion*** comprised four items, for instance, 'I spend less time with my family due to this technology.' Cronbach's α was.91. ***(3) T-complexity*** encompassed five items, including 'I do not know enough about this technology to handle my job satisfactorily.' Cronbach's α was.90. ***(4)*** The original ***t-insecurity*** consisted of five items, including 'I feel a constant threat to my job security due to new technologies.' However, during confirmatory factor analysis (CFA), one item, 'I have to constantly update my skills to avoid being replaced,' exhibited low loading (.150). As a result, only four items were included in the final analysis model (see Appendix B). The Cronbach's α of the four items was.79. ***(5) T-uncertainty*** consists of four items, including 'There are always new developments in the technologies we use in our organization.' Cronbach's α was.81. The Cronbach's α of the overall technostress from AI was.90.

Engagement (Time 2): The 9-item short version adapted from Schaufeli et al. (2002,2006) work was used. A sample item is 'At my work, I feel bursting with energy.' Cronbach's α was.92.

Exhaustion (Time 2): The five-item emotional exhaustion subscale from the Maslach Burnout Inventory–General Survey (MBI–GS) was adapted (Schaufeli et al.,1996). An example item is 'I feel burned out from work.' Cronbach's α was.93.

Productivity (Time 3): Tarafdar et al.'s (2007) four items were adapted for use; an example item is 'This technology helps improve the quality of my work.' Cronbach's α was.95. We used self-rated productivity measures instead of objective productivity measures reported in previous research (e.g., Brynjolfsson et al., 2023; Noy & Zhang, 2023; Peng et al., 2023) because the collection of data from various companies and industries makes it difficult to perform identical measurements.

Job Satisfaction (Time 3): This variable was measured via the 3-item overall job satisfaction scale from the Michigan Organizational Assessment Scale recommended by Bowling and Hammond (2008). An example item is 'All in all, I am satisfied with my job.' Cronbach's α was.87.

Work—Family Conflict (Time 3): Grandey et al.'s (2005) self--reported work interference with family scale, with six items, was adapted for use. A sample item is 'My job keeps me from spending time with my spouse or partner' and 'When I get home from my job, I do not have the energy to do work around the house.' Cronbach's α was.92.

4.2.2. Control variables

In our analysis, we consider several demographic variables, including gender, age, education, marital status, having children, and organizational tenure, as control factors. Previous research has suggested that AI impacts the psychological well-being of men more than it does women (Wei & Li, 2022) and that gender significantly influences work—family conflict, with women experiencing more conflict than men do (Van Daalen et al., 2006). Additionally, age differences reveal variations in digital literacy and proficiency in using ICTs (Elena-Bucea et al., 2021; O'Bannon & Thomas, 2014), with younger individuals exhibiting greater digital competence. Moreover, education and skill levels are pivotal factors influencing employees' job satisfaction, with the negative impact being more pronounced for highly qualified and skilled workers (Schwabe & Castellacci, 2020). AI tends to benefit highly skilled and educated workers more than it does lower-skilled and less educated workers (Bankins et al., 2024; Fossen & Sorgner, 2022). Furthermore, research in the work—life balance domain indicates that families with marriages and children are more likely to experience work—family conflicts (French et al., 2018). Therefore, we include these variables as covariates to reduce alternative explanations.

In addition, we included 'The duration of AI adoption at work' as another control variable. The participants indicated their response to the question 'How long have you been using AI in your work?' (1 =For the last 3 months, 2 =For the last 6 months, 3 =From 6 months to 1 year, 4 =From 1 year to 2 years, and 5 =More than 2 years).

4.3. Analysis strategy

We began our data analysis with a confirmatory factor analysis (CFA) in Mplus 8.6 to evaluate distinct constructs represented by the variables. This included establishing efficacy and technostress from AI as higher-order factors. Higher-order factors encapsulate and represent the interrelationships among lower-order factors, which are calculated from observed items (Brown, 2015). For hypothesis testing, we utilized Bayesian structural equation modeling (BSEM) following Asparouhov et al.'s (2015) guidelines. Empirically, BSEM offers a more flexible and comprehensive modeling framework that is beneficial for handling parameter uncertainty, estimating complex models, and conducting hypothesis testing (Stromeyer et al., 2015; Van de Schoot et al., 2017). In BSEM, we used noninformative priors because we lacked prior knowledge of the issue, and we followed Cain and Zhang's (2019) suggestion to choose a model with less misspecification.

5. Results

The initial step involves CFA to validate the distinct constructs (efficacy, technostress, engagement, exhaustion, productivity, job satisfaction, and work–family conflict) included in the study. Initially, we calculated all observable variables into their latent variables. The results represent distinct constructs of the study variables. However, we found that one observable variable had lower loadings (.150). Consequently, we decided to delete it (Model 2, Table 2). Additionally, we observed that t-uncertainty had lower loadings (.125) under technostress (see Appendix B). Therefore, we separated it from technostress when calculating the results (Model 3, Table 2). A comparison of the models in Table 2 showed that Model 3 achieved better CFI, TLI, RMSEA, and SRMR values than those of the other models; therefore, we selected Model 3 as the best-fitting model and proceeded with the following analysis.

Table 3 displays the descriptive statistics of the study. The preliminary observations of the table indicate that the relationship between t-uncertainty and technostress from AI reveals a nonsignificant correlation (.06); therefore, separating t-uncertainty from technostress appears to be appropriate. Additionally, generative AI is found to be correlated with gender, educational level, organization tenure, and duration of AI adoption. The preliminary assessment is that males use generative AI more than females do, individuals with higher educational levels use it more than those with lower educational levels do, new employees use it more than senior employees do, and adoption duration seems to be shorter.

5.1. Main theoretical hypotheses

We employed BSEM to test our hypotheses. Given the distinction between t-uncertainty and technostress, we constructed serial models (see Table 4), including variations that excluded t-uncertainty (see Fig. 2) and those that integrated it under different conditions (see Appendix C). All BSEMs demonstrated an RMSEA of less than.06, indicating an excellent fit (Garnier-Villarreal & Jorgensen, 2020; Hong et al., 2024). Cain and Zhang (2019) proposed that thresholds of $PPP < .10$ and $\Delta DIC > 7$ (when comparing two models) effectively ensure low false detection rates and precise model selection. Additionally, a smaller DIC indicates a better fit than alternative models (Lee & Song, 2012; Spiegelhalter et al., 2002). We observed that the model without t-uncertainty (Model 1, Table 4) yielded the best results. However, when t-uncertainty was included, Model 5 presented a smaller DIC than

Table 2
Comparison of CFA Results for Studied Variables.

	X^2 (df)	CFI	TLI	RMSEA	SRMR	Best Choice
Model 1: Original	3703.101 (1511)	.913	.908	.049	.077	
Model 2: Deletion of one low loading item from t-insecurity	3499.938 (1456)	.918	.914	.048	.075	
Model 3: Separation of t-uncertainty from technostress	3411.360 (1450)	.922	.917	.047	.062	✓
Model 4: Combination of t-uncertainty with efficacy	3446.266 (1456)	.921	.916	.048	.064	

Note. All the models consisted of seven factors: efficacy, technostress, engagement, exhaustion, productivity, job satisfaction, and work–family conflict. Efficacy and technostress were higher-order factors. Efficacy included both usefulness and reliability. Technostress includes t-overload, t-invasion, t-complexity, t-insecurity, and t-uncertainty.

Models 2–4 did (see Table 4). The results of Model 5 closely aligned with Model 1, supporting the original theoretical framework. We present the primary findings of Model 1 and provide supplementary results for Model 5 in Appendix C.

Fig. 2 illustrates the impact of excluding the t-uncertainty effect (refer to Model 1, Table 4). The results indicate that generative AI exhibited a negative association with technostress from AI ($\gamma = -0.19$, $p < .01$), with the 95 % CI (−0.268, −0.104) excluding zero. However, AI efficacy did not significantly impact technostress from AI ($\gamma = -0.02$, p = ns), with the 95 % CI (−0.132, 0.092) encompassing zero, supporting Hypothesis 1(b).

With respect to the ability of AI efficacy and generative AI to predict outcome variables, both AI efficacy ($\gamma = 0.81$, $p < .01$, 95 % CI=0.695, 0.948) and generative AI ($\gamma = 0.07$, $p < .05$, 95 % CI=0.002, 0.138) were positively associated with productivity, with the 95 % CIs excluding zero. However, they were not directly related to job satisfaction ($\gamma = 0.06$, p = ns., 95 % CI = −0.046, 0.172; $\gamma = -0.03$, p = ns., 95 % CI = −0.098, 0.040, respectively) or work–family conflict ($\gamma = 0.02$, p = ns., 95 % CI = −0.093, 0.138; $\gamma = -0.00$, p = ns., 95 % CI = −0.077, 0.070, respectively), with the 95 % CI including zero; thus, only Hypotheses 2(a) and 3(a) were supported.

In addition, AI technostress was found to be positively associated with work–family conflict ($\gamma = 0.18$, $p < .01$), with the 95 % CI (0.091, 0.262) excluding zero. However, AI technostress did not have a significant relationship with productivity ($\gamma = 0.03$, p = ns., 95 % CI = −0.055, 0.122) or job satisfaction ($\gamma = -0.04$, p = ns., 95 % CI = −0.115, 0.044), with the 95 % CI including zero. The results supported only Hypothesis 4(c).

Additionally, BSEM revealed that technostress positively impacted exhaustion ($\gamma = 0.33$, $p < .01$, 95 % CI = 0.242, 0.412), and AI efficacy negatively affected exhaustion ($\gamma = -0.16$, $p < .01$, 95 % CI = −0.270, −0.054), with the 95 % CI excluding zero. Generative AI did not impact exhaustion ($\gamma = 0.02$, p = ns., 95 % CI = −0.077, 0.070). In turn, exhaustion was positively associated with productivity ($\gamma = 0.14$, $p < .01$, 95 % CI = 0.051, 0.224) and work–family conflict ($\gamma = 0.50$, $p < 0.01$, 95 % CI = 0.412, 0.570) and negatively predicted job satisfaction ($\gamma = -0.34$, $p < .01$, 95 % CI = −0.417, −0.254), with the 95 % CI excluding zero.

Moreover, the results revealed that only AI efficacy was positively associated with engagement ($\gamma = 0.50$, $p < 0.01$), with a 95 % CI (0.399, 0.601) excluding zero. In contrast, generative AI ($\gamma = 0.45$, p = ns., 95 % CI = −0.041, −0.131) and AI technostress ($\gamma = 0.04$, p = ns., 95 % CI = −0.041, −0.118) did not significantly influence engagement, as their 95 % CIs included zero. In turn, engagement was positively associated with only job satisfaction ($\gamma = 0.54$, $p < 0.01$), with the 95 % CI (0.451, 0.630) excluding zero. However, engagement did not influence productivity ($\gamma = 0.03$, p = ns., 95 % CI = −0.103, 0.133) or work–family conflict ($\gamma = -0.01$, p = ns., 95 % CI = −0.108, 0.094), with the 95 % CIs including zero.

5.2. Mediating effects

On the basis of the above results, we examined the associations between significant paths, as reported in Table 5. The analysis of significant mediating effects revealed important relationships among the variables, as determined through Bayesian estimation. Excluding t-uncertainty, we find that efficacy positively influences engagement, which in turn enhances job satisfaction (effect = 0.437, 95 % CI = 0.329, 0.561), supporting Hypothesis 6(b). AI technostress was shown to positively affect productivity (effect = 0.041, 95 % CI = 0.019, 0.067) and work–family conflict (effect = 0.146, 95 % CI = 0.106, 0.188) while negatively affecting job satisfaction (effect = −0.101, 95 % CI = −0.135, −0.071) via exhaustion, supporting H8. Serial mediations indicated that generative AI negatively impacted productivity through AI technostress and exhaustion (effect = −0.017, 95 % CI = −0.031, −0.007), while it positively affected job satisfaction (effect = 0.043, 95 % CI = 0.024, 0.066) and negatively affected work—family conflict (effect = −0.062, 95 % CI = −0.093, −0.035), supporting Hypothesis 10.

We conducted additional mediation analyses not included in the original hypotheses, including the finding that generative AI negatively affected work–family conflict through technostress (effect = −0.068, 95 % CI = −0.109, −0.033). One of the most interesting findings was that AI efficacy influenced productivity (effect = −0.038, 95 % CI = −0.079, −0.009), job satisfaction (effect = 0.088, 95 % CI = 0.037, 0.146), and work—family conflict (effect = −0.128, 95 % CI = −0.211, −0.054) via exhaustion.

6. Discussion

Our research aims to enhance the understanding of the light and shadow aspects of AI adoption in the workplace and its impact on employees' work and life domains, including productivity, job satisfaction, and work–family conflict. Drawing upon the JD–R model, we classify AI efficacy and generative AI as resources while identifying AI technostress as a demand. We also investigate the psychological processes of engagement and exhaustion.

Our study's initial findings support the idea that generative AI helps reduce the technostress associated with AI adoption (Hypothesis1(b); see Fig. 2). Specifically, AI-induced technostress directly contributes to negative outcomes such as work–family conflict (Hypothesis 4(c)) and psychological exhaustion, which in turn affect other work-related outcomes (Hypothesis (8)). Our results suggest that generative AI may alleviate the negative strain of technostress more effectively than non-generative AI. In other words, generative AI may serve as a more effective job resource in mitigating the job demands associated with technostress resulting from AI adoption than nongenerative AI. The serial mediation relationships among generative AI, technostress, exhaustion, and productivity (Hypothesis 10(a)) were significant (see Table 5), implying that generative AI may help mitigate the adverse effects of technostress, which subsequently reduces exhaustion.

The impact of AI efficacy on productivity is significantly positive, and generative AI also significantly improves productivity. However, we did not find that engagement mediates the relationship between AI efficacy, generative AI (i.e., Hypothesis 6(a) and Hypothesis 7(a)) and productivity. Instead, exhaustion mediates the relationship between AI technostress and productivity (Hypothesis 8(a)). While AI-induced technostress decreases employees' energy levels, leading to

Table 3
Descriptive Statistics and Correlations.

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Gender	.50	.50	—														
2. Age	39.21	8.83	.09*	—													
3. Education	2.30	.50	.17**	−.08	—												
4. Marital status	.54	.50	.05	.51**	.04	—											
5. Have Children	.45	.50	.04	.57**	.00	.73**	—										
6. Organization Tenure	9.33	7.96	.03	.66**	−.13**	.41**	.44**	—									
7. AI Adoption Duration	2.84	1.26	−.06	.14**	.09*	.11**	.14**	.11**	—								
8. Generative AI	.46	.50	.20**	−.08	.13**	−.04	−.06	−.11**	−.19**	—							
9. Efficacy with AI	5.28	.83	−.07	−.03	.03	.00	−.01	−.06	.21**	−.12**	—						
10. Technostress with AI	3.35	.94	−.13**	.10*	−.16**	.11**	.10**	.16**	.05	−.20**	−.02	—					
11. T-uncertainty (separate from technostress)	4.28	1.12	.00	.04	.08*	.06	.06	.08*	.15**	−.09*	.34**	.06	—				
12. Exhaustion	3.90	1.24	−.02	−.21**	−.03	−.09*	−.13**	−.08	−.01	−.02	−.04	.33**	−.09*	—			
13. Engagement	4.38	.95	−.04	.21**	.02	.11*	.18**	.05	.03	−.03	.32**	.03	.25**	−.35**	—		
14. Productivity	4.99	1.05	.04	−.07	.04	−.09*	−.05	−.13**	.14**	−.01	.61**	−.00	.23**	.01	.32**	—	
15. Job Satisfaction	4.14	.54	−.05	.04	.07	.03	.05	−.03	.05	−.04	.25**	−.06	.28**	−.22**	.43**	.27**	—
16. Work–Family Conflict	3.35	1.21	−.07	−.12**	.04	−.06	−.07	−.04	−.03	−.04	−.01	.33	−.02	.51**	−.13**	−.06	−.15**

Note. n = 600 participants. For gender, 1 =male, 0 =female; for marriage, 0 = single, 1 =married; for having children, 0 =no, 1 =yes; for AI adoption duration, 1 =in the last 3 months, 2 =in the last 6 months, 3 =from 6 months to 1 year, 4 =from 1 year to 2 years, and 5 =more than 2 years; and for generative AI, 1 =yes, 0 =no. *$p < .05$; **$p < 0.01$, two-tailed test.

exhaustion, it still benefits productivity, suggesting that technostress indirectly benefits productivity (linked to Hypothesis (5)). This finding demonstrates that AI adoption at work genuinely improves employees' productivity, whether in terms of resources or demands.

Regarding AI's impact on job satisfaction, we did not observe a direct effect on employees' job satisfaction from AI efficacy, generative AI or AI technostress. Instead, both exhaustion and engagement were found to mediate the relationship between predictors and job satisfaction. The results suggest that AI efficacy positively influences job satisfaction by increasing engagement (Hypothesis 6(b)), whereas AI technostress negatively influences job satisfaction by causing exhaustion (Hypothesis 8(b)). Furthermore, the serial mediation relationships among generative AI, technostress, emotional exhaustion, and job satisfaction reveal a positive association (Hypothesis 10(b)). This finding indicates that both AI efficacy and generative AI increase employees' job satisfaction, despite technostress inducing negative effects on job satisfaction through exhaustion.

In terms of the impacts of AI on work—family conflict, AI technostress directly increases work—family conflict (Hypothesis 4(c)) and indirectly increases it through exhaustion (Hypothesis 8(c)). However, our analysis of the serial mediation relationships among generative AI, AI technostress, emotional exhaustion, and work–family conflict reveals a negative association (Hypothesis 10(c)). This finding indicates that generative AI adoption could decrease work—family conflict by reducing technostress and subsequent emotional exhaustion. We summarize the hypothesis results in Table 6.

Another important finding is that 't-uncertainty' (i.e., updating of software and equipment) might be considered a factor distinct from technostress; therefore, 't-uncertainty' should not be treated as a demand. Indeed, t-uncertainty was positively associated with AI efficacy, AI technostress, and job satisfaction, while being negatively associated with exhaustion and productivity (see Appendix C). The results align with those of Yuan et al. (2023), Gerdiken et al. (2021), and Aktan and Toraman (2022), indicating that t-uncertainty exhibits a distinct pattern from technostress.

In addition, we found an intriguing pattern regarding the influence of AI adoption duration on AI efficacy and engagement (see Appendix C Table A). The results indicate that as time progresses, the impact of AI efficacy becomes more pronounced ($\gamma = 0.22$, $p < .01$). However, employees seem to decrease their engagement as the duration of AI adoption increases ($\gamma = -0.14$, $p < .01$). It appears that with the longer implementation of AI, there is a negative effect on employees' engagement. This finding might suggest that the path from AI efficacy to engagement and subsequent job satisfaction may gradually diminish over time, but more evidence is needed. Therefore, further studies are needed to explore this additional finding. Additionally, job tenure is positively related to AI technostress, suggesting that longer-tenured employees may experience more technostress. This implies that even employees with longer tenure still need to adapt their new work methods and become familiar with the operation of new AI technologies.

Furthermore, while our hypotheses did not anticipate interactions between resource-based variables, some may argue that generative AI could influence AI efficacy. To explore this possibility, we conducted additional analyses. First, a multiple-group analysis examined differences between the generative AI and non-generative AI groups within our hypothesized model. However, we observed no significant patterns distinguishing the two groups. Then, we incorporated a dummy variable (representing generative AI vs. non-generative AI) into the model and identified a negative relationship between generative AI and AI efficacy, consistent with the results ($r = -0.12$) shown in Table 3. We further calculated the model using generative AI to predict usefulness and reliability. The results indicated no significant influence of generative AI on usefulness ($\gamma = -0.08$, p = n.s.); however, generative AI had a significant negative impact on reliability ($\gamma = -0.22$, $p < 0.01$). This result suggests that generative AI may undermine AI efficacy by producing irrelevant or incorrect information, requiring users to expend additional

Table 4
Comparison for BSEM Model Selection.

Model	Descriptions	PPP	CFI	TLI	RMSEA	DIC	Best Choice	
1	Excluding t-uncertainty in the model	> .001	.918	.912	.045	82788.798	✓	Theoretical Model
2	Including t-uncertainty as a factor of technostress	> .001	.909	.903	.046	90382.694		Results similar to Model 1
3	T-uncertainty is distinct from technostress and predicts mediator and outcome variables.	> .001	.911	.904	.045	90365.063		
4	T-uncertainty predicts efficacy, technostress and other variables.	> .001	.913	.906	.045	90303.162		
5	Generative AI predicts t-uncertainty, which in turn predicts efficacy, technostress, and other variables	> .001	.913	.906	.045	90301.105	✓	See Appendix C

Note. PPP represents the posterior predictive p value, and DIC represents the deviance information criterion. We base the selection on the smaller DIC (Lee & Song, 2012; Spiegelhalter et al., 2002) and better model fit indices to choose models. When the sample size is large and there are many minor discrepancies between the model and the data, the PPP value is typically nearly 0. If the model fit indices (i.e., CFI, TLI, and RMSEA) indicate a good fit, the model can still be considered appropriate. Using these approximate fit indices helps in constructing a BSEM that better matches the actual data, thus avoiding complications from adding too many parameters or using larger priors (Asparouhov & Muthén, 2021).

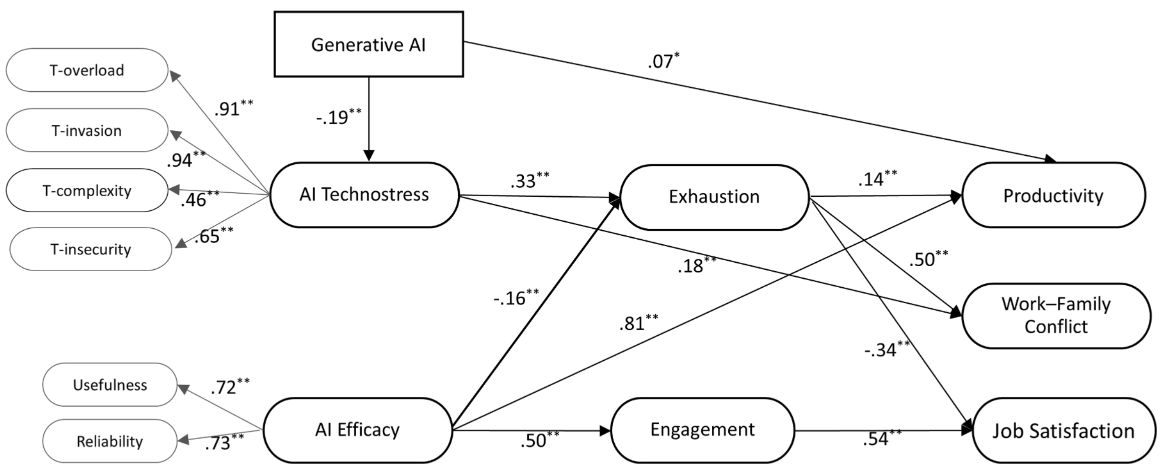

Fig. 2. Significant Paths of the BSEM Results (excluding t-uncertainty). Note. Please refer to Table 4, Model 1. To maintain conciseness, the control variables (gender, age, education, marital status, having children, job tenure, and AI adoption duration) and observed variables are not displayed, revealing only the latent variables. The combined t-uncertainty results are shown in Appendix C. $*p < .05$; $^{**}p < .01$.

effort on evaluation, and thereby reducing overall efficiency.

Additionally, we found that generative AI influenced technostress, whereas AI efficacy did not. This suggests that unmeasured factors distinguishing generative AI from nongenerative AI may reduce technostress beyond the scope of the AI efficacy we measured. These factors, which may include ease of use for content generation (Fui-Hoon Nah et al., 2023) and the provision of personalized learning opportunities (Morandini et al., 2023), help alleviate technostress. This highlights the additional potential of generative AI compared to non-generative AI, which warrants further exploration.

6.1. Theoretical contributions

Our research contributes to the literature by providing empirical data that address the advantages and drawbacks of AI adoption in the workplace. We utilized the JD–R model to investigate the dual impact of AI adoption, distinguishing between resources (generative AI and efficacy) and demands (technostress), thereby offering insights into how AI influences employees' productivity, job satisfaction, and work–family conflict in real-world settings.

Our results reveal that AI-related resources (AI efficacy and generative AI) and demands (AI technostress) contribute to the complex pathways that address the potential paradox of AI's impact on productivity and job satisfaction (Bäck et al., 2022; Bhargava et al., 2021). We propose a pathway relationship between AI resources and demands on productivity, showing that AI adoption significantly increases productivity either directly through AI efficacy and generative AI or indirectly through technostress. Moreover, our research model indicates that technostress, which causes exhaustion, negatively impacts job satisfaction and increases work–family conflict. Conversely, the efficacy of AI positively influences job satisfaction by increasing engagement. Echoing the JD–R model, job demands and resources trigger two different processes: the health impairment process and the motivational process (Bakker et al., 2023). Job demands trigger the health impairment process, leading to diminished well-being. Conversely, job resources activate the motivational process, fostering higher engagement and improved performance while buffering the impact of job demands.

Importantly, our study is the first to compare generative AI with nongenerative AI in the workplace, revealing the benefits of generative AI in reducing technostress. While technostress from AI has a direct or indirect negative effect on work—family conflict, our research suggests that generative AI helps mitigate this impact by reducing technostress-induced exhaustion, which in turn reduces work—family conflict and increases job satisfaction. These empirical findings are significant given the widespread adoption of generative AI in the workplace since late 2022.

6.2. Practical implications

As intelligent systems continue to evolve and garner wider acceptance within organizations, especially generative AI, there is potential for a revolutionary impact on fields and industries that rely on creativity, innovation, and knowledge processing (Feuerriegel et al., 2024). This evolution will redefine employee roles, potentially leading to a

Table 5
Significant Mediating Effects with Bayesian Estimation.

Indirect Paths	Effect	95 % CI		
		Lower	Upper	
Excluding t-uncertainty				
AI Efficacy→ Engagement→ Job Satisfaction	.437	.329	.561	Hypothesis 6(b)
AI technostress→ Exhaustion→ Productivity	.041	.019	.067	Hypothesis 8(a)
AI technostress→ Exhaustion→ Job Satisfaction	−.101	−.135	−.071	Hypothesis 8(b)
AI technostress→ Exhaustion→ Work–Family Conflict	.146	.106	.188	Hypothesis 8(c)
Serial mediations				
Generative AI→ AI Technostress→ Exhaustion→ Productivity	−.017	−.031	−.007	Hypothesis 10(a)
Generative AI→ AI Technostress→ Exhaustion→ Job Satisfaction	.043	.024	.066	Hypothesis 10(b)
Generative AI→AI Technostress→ Exhaustion→ Work–Family Conflict	−.062	−.093	−.035	Hypothesis 10(c)
Other mediations not included in the hypotheses				
Generative AI→ AI Technostress→ Work–Family Conflict	−.068	−.109	−.033	
AI Efficacy→ Exhaustion→ Productivity	−.038	−.079	−.009	When integrating t-uncertainty, the effect from AI efficacy to exhaustion disappears
AI Efficacy→ Exhaustion→ Job Satisfaction	.088	.037	.146	
AI Efficacy→ Exhaustion→ Work–Family Conflict	−.128	−.211	−.054	

Note. The estimation was conducted with unstandardized coefficients.

more complex AI–employee dynamic (Makarius et al., 2020), ultimately affecting employees' work and life domains. Our study provides a framework for administrators and managers to navigate the positive and negative impacts of AI adoption. The positive aspects of AI can serve as job resources, increasing employee productivity and job satisfaction while reducing work–family conflict. However, the technostress associated with AI adoption may undermine these benefits by depleting employees' psychological resources and causing exhaustion, which significantly affects their overall well-being. From a technological perspective, our study indicates that the generative AI may be more beneficial in mitigating the negative effects of technostress associated with AI adoption. From a management standpoint, leaders can implement administrative measures to alleviate exhaustion, such as updating software and equipment to reduce uncertainty and fostering positive supervision (e.g., Chuang et al., 2022), both of which have been shown to decrease employee exhaustion and lessen the adverse effects of technostress.

Moreover, to mitigate the negative impacts resulting from uncertainties associated with AI, which are currently evident, companies should adopt social responsibility measures aimed at safeguarding the well-being of employees in future AI collaborations. For example, they should actively promote training and reskilling initiatives. This approach ensures that employees facing the possibility of future displacement can acquire new skills, thereby enhancing their ability to collaborate with intelligent machines (Schwabe & Castellacci, 2020). Bhargava et al. (2021) highlighted that human interaction and interpersonal skills (such as communication and emotional intelligence) remain invaluable and cannot be replicated by AI, thus emphasizing the importance of employees strengthening these unique skills.

Table 6
Summary of Hypotheses from the Results.

Hypotheses		Supported
H1	(a) AI Efficacy is negatively associated with technostress with AI at work.	–
	(b) Generative AI adoption is negatively associated with technostress with AI at work.	Yes
H2	Efficacy with AI adoption at work is …	
	positively associated with (a) productivity.	Yes
	positively associated with (b) job satisfaction.	–
	negatively associated with (c) work–family conflict	–
H3	Generative AI adoption at work is …	
	positively associated with (a) productivity.	Yes
	positively associated with (b) job satisfaction.	–
	negatively associated with (c) work–family conflict	–
H4	Technostress with AI adoption at work is …	
	negatively associated with (a) productivity.	–Only t-uncertainty
	negatively associated with (b) job satisfaction.	–
	positively associated with (c) work–family conflict	Yes
H5	Technostress with AI adoption at work is not negatively associated with…	
	(a) productivity	–Not direct but indirect, linked to H8(a)
	(b) job satisfaction; instead, it has either a positive association or no influence.	–Only t-uncertainty
H6	Efficacy with AI adoption at work is positively related to engagement, and engagement mediates the relationships between efficacy and…	
	(a) productivity	–
	(b) job satisfaction	Yes
	(c) work–family conflict	–
H7	Generative AI adoption at work is positively related to engagement, and engagement mediates the relationships between generative AI and (a) productivity, (b) job satisfaction, and (c) work–family conflict.	–
H8	Technostress with AI adoption at work is positively related to exhaustion, and exhaustion mediates the relationships between technostress and…	
	(a) productivity	Yes
	(b) job satisfaction	Yes
	(c) work–family conflict	Yes
H9	Efficacy with AI is associated with (a) productivity, (b) job satisfaction, and (c) work–family conflict via the chain of AI technostress and exhaustion.	–
H10	Generative AI adoption is associated with (a) productivity via the chain mediation of AI technostress and exhaustion.	Yes
	Generative AI is associated with (b) job satisfaction via the chain of AI technostress I and exhaustion.	Yes
	Generative AI is associated with (c) work–family conflict via the chain of AI technostress and exhaustion.	Yes

Furthermore, many companies dedicate significant time, effort, and resources to AI, only to discover that the anticipated benefits remain elusive and ultimately label AI initiatives as failures (Canhoto & Clear, 2020; Fountaine et al., 2019). Wirtz et al. (2023) suggested that such challenges can be addressed through organizational flexibility, particularly when implementing digital service technologies, enabling companies to navigate conflicting demands and achieve cost-effective service excellence. However, Makarius et al. (2020) emphasized that organizations frequently deploy AI without careful consideration of the employees who collaborate with it, thereby diminishing the value of AI cooperation with the organization. Consequently, it is imperative for businesses to comprehend the potential benefits and risks that AI may pose and its impact on organizational behavior to leverage the advantages of technology.

6.3. Limitations and future directions

This study offers insights into AI adoption and its impact on workers' work–life well-being, although it is not without limitations. First, the measurement instrument of this study uses self-rated, time-lagged surveys, and generative AI was evaluated via an independent rater for coding. Although this approach aims to mitigate self-reported bias (Donaldson & Grant-Vallone, 2002), it may not completely eliminate it. Subsequent research endeavors should gather data from various sources, including coworkers, spouses, and supervisors, to mitigate bias.

Second, unmeasured factors distinguishing generative AI from nongenerative AI may significantly reduce technostress beyond the scope of the AI efficacy measured in this study. Future research could investigate factors like the ease of content generation and the availability of personalized learning opportunities, as these may help reduce technostress—especially related to job replacement—by exploring whether individuals who can use AI are less concerned about being replaced.

Third, although we used BSEM to calculate the results, importantly, the data are correlational in nature. Future studies should consider the use of experimental designs to explore these relationships further and draw causal explanations. Researchers can also adopt an experimental design to compare the effects of generative AI versus nongenerative AI on participants' outcomes.

Fourth, although we collected data from a wide range of industries and companies, the sample pool is still limited to Taiwan, which is in East Asia and has a more collective culture than individualistic cultures such as those in Europe and America. This limitation impacts the generalizability of the findings and encourages the collection of samples from different countries to understand the influence of culture.

Additionally, our research potentially identified trends in the data, suggesting that the intelligence and usability of AI have reduced employees' engagement with their work over time. In other words, the usability of AI may increase as workers disengage. To gain a deeper understanding of this relationship, a longitudinal study tracking employee engagement before and after the implementation of AI in a company would be beneficial. Such research could provide valuable insights into the long-term impact of AI on workplace dynamics.

Moreover, certain employees might face challenges in establishing trust with a system or teammate that lacks emotional or empathetic capabilities. Future studies should explore how employees' emotional interactions with AI influence their work or personal lives.

Finally, generative AI may provide misleading information in a consequential environment (Allen & Weyl, 2024). If generative AI dominates as the main support for decision-making by employees or managers, there is a need for more consideration of how to validate the data or information from generative AI.

7. Conclusion

This study aims to investigate and understand how the light and shadow aspects of AI truly impact employees' work and lives through the lens of the JD–R model's resources and demands perspective. Our study focuses on the broader implications of AI adoption for employees' overall work—life domains rather than solely concentrating on human—machine collaboration applications. We provide empirical research integrated with the JD–R model theoretical framework, contributing to leading research on the impact of AI on employee well-being.

CRediT authorship contribution statement

Chuang Ya-Ting: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Chiang Hua-Ling:** Writing – review & editing, Project administration, Data curation, Conceptualization. **Lin An-Pan:** Writing – review & editing, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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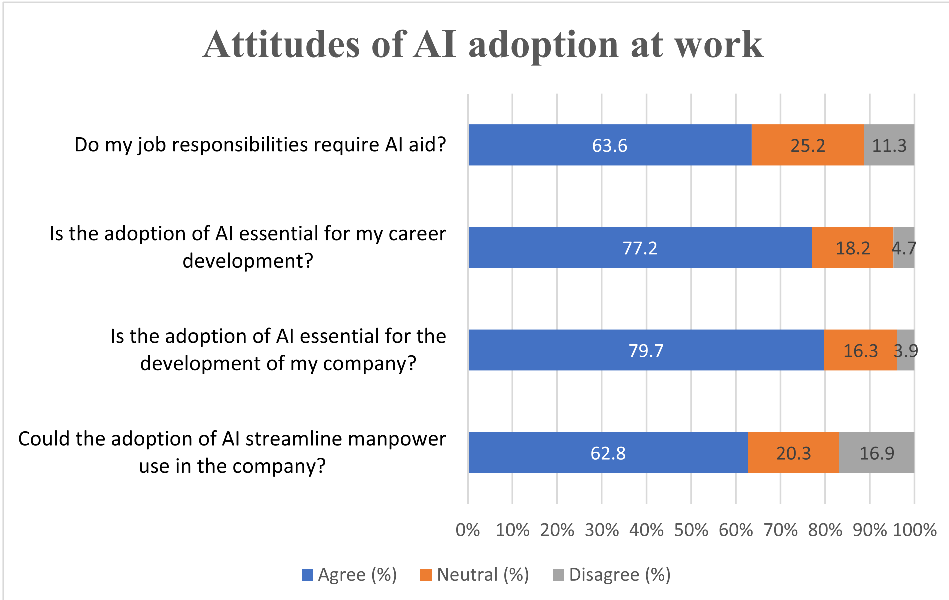
Appendix A



Note. N=600 employees (gender balanced). To understand employees' basic opinions on AI adoption at work, we asked four questions that were not included in our main research framework at Time 1.

Appendix B

Observable variable loadings of CFA

Indicator	Loading	Indicator	Loading	Indicator	Loading	Indicator	Loading	Indicator	Loading
Efficacy with AI		***Usefulness***		***T-complexity***		***Engagement***		***Productivity***	
Usefulness	.748	US1	.817	TECX1	.689	ENG1	.850	PD1	.902
Reliability	.736	US2	.858	TECX2	.802	ENG2	.853	PD2	.934
		US3	.885	TECX3	.743	ENG3	.901	PD3	.891
Technostress with AI		US4	.814	TECX4	.897	ENG4	.821	PD4	.914
T-overload	.911	***Reliability***		TECX5	.862	ENG5	.624	***Job satisfaction***	
T-invasion	.937	RE1	.864	***T-insecurity***		ENG6	.571	WS1	.788
T-complexity	.454	RE2	.895	TEI1	.644	ENG7	.736	WS2	.876
T-insecurity	.647	RE3	.810	TEI2 ▲	.150	ENG8	.843	WS3	.856
T-uncertainty▲	.125	***T-overload***		TEI3	.578	ENG9	.662	***Work–Family Conflict***	
		TEO1	.852	TEI4	.762	***Exhaustion***		WFC1	.728
		TEO2	.868	TEI5	.782	EX1	.814	WFC2	.835
		TEO3	.778	***T-uncertainty***		EX2	.855	WFC3	.819
		TEO4	.768	TEU	.472	EX3	.867	WFC4	.864
		TEO5	.634	TEU	.766	EX4	.861	WFC5	.809
		T-invasion		TEU	.851	EX5	.830	WFC6	.850
		TEI1	.741	TEU	.766				
		TEI2	.914						
		TEI3	.904						
		TEI4	.859						

Note. We deleted indicator TEI2 for the model calculations (▲ indicates the loading was below an acceptable level).

Appendix C.

T-uncertainty Impact

In addition to our main hypotheses, we integrate t-uncertainty (see Figure A below) into the model as an indicator (refer to Model 5, Table 4). The results showed that generative AI was negatively related to t-uncertainty ($\gamma = -0.09$, $p = .028$, 95 % CI = −0.128, 0.309), although the 95 % CI included zero. Additionally, t-uncertainty was positively related to efficacy ($\gamma = 0.42$, $p < 0.01$, 95 % CI = 0.323, 0.519), technostress ($\gamma = 0.13$, $p < 0.01$, 95 % CI = 0.022, 0.240), and job satisfaction ($\gamma = 0.10$, $p < 0.01$, 95 % CI = 0.011, 0.188) and negatively related to exhaustion ($\gamma = -0.12$, $p < 0.01$, 95 % CI = −0.223, −0.012) and productivity ($\gamma = -0.14$, $p < 0.01$, 95 % CI = −0.247, −0.030), with the 95 % CIs excluding zero. The other paths are reported in Table A below.

When t-uncertainty was integrated, the results demonstrated that t-uncertainty influenced exhaustion, which in turn negatively affected productivity (effect = −0.021, 95 % CI = −0.044, −0.004) and work–family conflict (effect = −0.095, 95 % CI = −0.017, −0.022) but positively affected job satisfaction (effect = 0.064, 95 % CI = 0.015, 0.117). However, when technostress was included in the chain mediation (i.e., t-uncertainty influencing outcomes via both technostress and exhaustion), the results revealed a positive effect on productivity (effect = 0.009, 95 % CI =0.001, 0.019) and work—family conflict (effect = 0.036, 95 % CI = 0.010, 0.066) but a negative effect on job satisfaction (effect = −0.024, 95 % CI = −0.045, −0.007). Furthermore, t-uncertainty positively impacted technostress, which in turn influenced work–family conflict (effect = 0.038, 95 % CI

= 0.009, 0.074). It also positively impacted AI efficacy, enhancing productivity (effect = 0.333, 95 % CI = 0.095, 0.599) and mediating the relationship between efficacy and engagement, leading to job satisfaction (effect = 0.167, 95 % CI = 0.108, 0.204). These findings underscore the complex interactions between AI-related factors and outcomes, highlighting both positive and negative pathways influenced by various mediators.

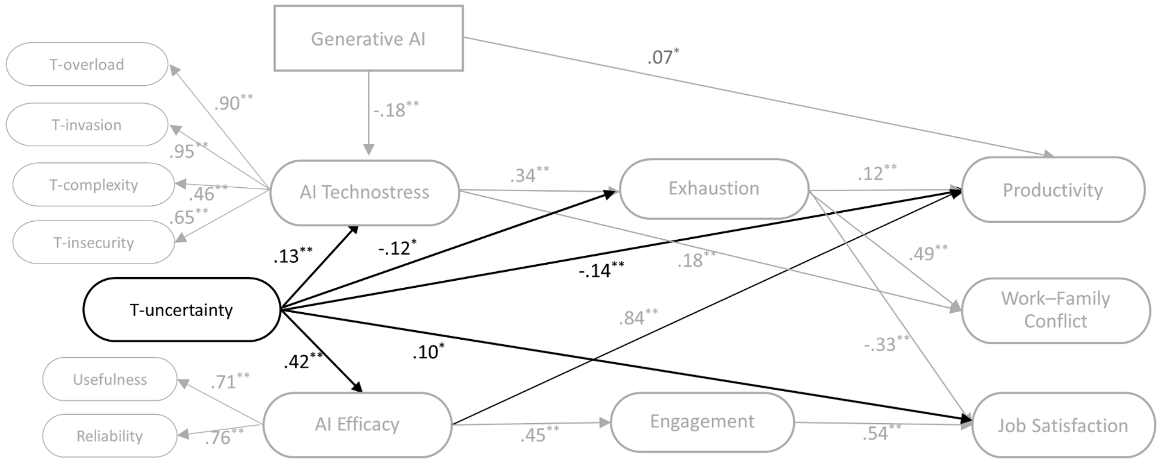


Fig. A. *Significant Paths of the BSEM Results (integrating t-uncertainty). Note.* Please refer to Table 4, Model 5. For brevity, the results of the original theoretical model (similar to Fig. 2) are represented in light color, and the control variables and observed variables are not displayed. For the statistics of the control variables, see Appendix C Table A. $^{+}p < .10$; $^{*}p < .05$; $^{**}p < .01$

Table A
BSEM results of Model 5, Table 4

	AI Technostress	AI Efficacy	T-uncertainty	Exhaustion	Engagement	Productivity	Job Satisfaction	Work–Family Conflict
Control variables								
Gender	−.08	−.09*	.04	.04	−.06	.12**	−.05	−.06
Age	−.03	.04	−.18	−.27**	.28**	.03	−.04	.01
Education	−.08*	−.01	.19	.01	.03	.00	.03	.09*
Marriage	.12**	.03	−.02	.01	−.11	−.14**	.02	−.04
Have Children	−.02	−.05	−.02	−.05	.17**	.08	−.01	.01
Job Tenure	.11**	−.16**	.08	.06	−.12**	−.04	.00	−.00
AI Adoption Duration	.01	.22**	.02	.07	−.14**	−.05	−.03	−.06
Main effect								
Generative AI	−.18**	—	−.09	.02	.04	.07*	−.03	.00
AI Efficacy	−.07	—	—	−.09	.45**	.84**	.02	.02
AI Technostress	—	—	—	.34**	.03	.05	−.05	.18**
T-uncertainty	.13**	.42**	—	−.12*	.08	−.14*	.10*	−.00
Exhaustion						.12**	−.33**	.49**
Engagement						.05	.54**	−.01
R^2	.12**	.28**	.05**	.20**	.30**	.65**	.52**	.35**

Note. n = 600 participants. $^{+}p < .10$;$^{*}p < .05$; $^{**}p < .01$. The entries are standardized model results.

Table B
Significant Mediating Effects with Bayesian Estimation

Indirect Paths	Effect	95 % CI	
		Lower	Upper
Integrating t-uncertainty			
T-uncertainty→ Exhaustion→ Productivity	−.021	−.044	−.004
T-uncertainty→ Exhaustion→ Job Satisfaction	.064	.015	.117
T-uncertainty→ Exhaustion→ Work–Family Conflict	−.095	−.017	−.022
T-uncertainty→ AI Efficacy→ Productivity	.333	.095	.599
T-uncertainty→ AI Technostress→ Work–Family Conflict	.038	.009	.074
Serial mediations			
T-uncertainty→ AI Efficacy→ Engagement→ Job Satisfaction	.167	.108	.240
T-uncertainty→ AI Technostress→ Exhaustion→ Productivity	.009	.001	.019
T-uncertainty→ AI Technostress→ Exhaustion→ Job Satisfaction	−.024	−.045	−.007
T-uncertainty→ AI Technostress→ Exhaustion→ Work–Family Conflict	.036	.010	.066

Note. The estimation was conducted with unstandardized coefficients.

Data availability statements

The data that support the findings of this study are available from the author upon reasonable request.

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