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ORIGINAL RESEARCH

Does AI-Driven Technostress Promote or Hinder Employees' Artificial Intelligence Adoption Intention? A Moderated Mediation Model of Affective Reactions and Technical Self-Efficacy

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Purpose: The increasing integration of Artificial Intelligence (AI) within enterprises is generates significant technostress among employees, potentially influencing their intention to adopt AI. However, existing research on the psychological effects of this phenomenon remains inconclusive. Drawing on the Affective Events Theory (AET) and the Challenge–Hindrance Stressor Framework (CHSF), the current study aims to explore the "black box" between challenge and hindrance technology stressors and employees' intention to adopt AI, as well as the boundary conditions of this mediation relationship.

Methods: The study employs a quantitative approach and utilizes three-wave data. Data were collected through the snowball sampling technique and a structured questionnaire survey. The sample comprises employees from 11 distinct organizations located in Guangdong Province, China. We received 301 valid questionnaires, representing an overall response rate of 75%. The theoretical model was tested through confirmatory factor analysis and regression analyses using Mplus and the Process macro for SPSS.

Results: The results indicate that positive affect mediates the positive relationship between challenge technology stressors and AI adoption intention, whereas AI anxiety mediates the negative relationship between hindrance technology stressors and AI adoption intention. Furthermore, the results reveal that technical self-efficacy moderates the effects of challenge and hindrance technology stressors on affective reactions and the indirect effects of challenge and hindrance technology stressors on AI adoption intention through positive affect and AI anxiety, respectively.

Conclusion: Overall, our study suggests that AI-driven challenge technology stressors positively impact AI adoption intention through the cultivation of positive affect, while hindrance technology stressors impede AI adoption intention by triggering AI anxiety. Additionally, technical self-efficacy emerges as a crucial moderator in shaping these relationships. This research has the potential to make a meaningful contribution to the literature on AI adoption intention, deepening our holistic understanding of the influential mechanisms involved. Furthermore, the study affirms the applicability and relevance of Affective Events Theory (AET) and the Challenge-Hindrance Stressor Framework (CHSF). In practical terms, the research provides actionable insights for organizations to effectively manage employees' AI adoption intention.

Keywords: challenge and hindrance technology stressors, AI adoption intention, positive affect, AI anxiety, technical self-efficacy

Introduction

The extensive implementation of digital technologies has firmly positioned artificial intelligence (AI) as a catalyst in the ongoing technological revolution across various domains.[1] AI's impact reaches into realms such as business innovation, process transformation, value creation, competitive advantage, and intelligent decision-making.[2–4] This influence has prompted organizations to progressively integrate AI,[5] leading to heightened organizational efficiency, productivity, performance, and innovation.[6–10] According to a recent study, 80% of large corporations have already adopted AI,[11] underlining its

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pivotal role in contemporary business landscapes. However, changing technology requirements also lead to technostress among employees, posing challenges and hindrances. How to enhance the employee's AI adoption intention becomes the key in achieving competitive advantages among corporations.

Research on the antecedents of AI adoption intention has predominantly focused on frameworks such as the Technology Acceptance Model (TAM),[12] the Technology-Organization-Environment (TOE) framework,[13] and the Unified Theory of Acceptance and Use of Technology (UTAUT).[14] Key influencing factors identified in these studies encompass: 1). environmental factors: including competitive pressure and social influence.[15,16] 2). technological factors: involving technical knowledge[4,17] (e.g., technology readiness and awareness, technological familiarity), and technical characteristics[4,17–19] (e.g., perceived ease of use, perceived usefulness). 3). organizational factors: encompassing facilitating conditions and subjective norms.[4,16] 4). individual-related factors: involving personality traits (e.g., self-efficacy, personal innovativeness),[20,21] and emotions (e.g., job insecurity,[22] AI anxiety[23]). While past research has explored factors influencing employees' AI adoption intention, only a few studies have investigated AI adoption as a source of stress, with inconclusive findings. Therefore, to bridge this gap, this study aims to explore the influence mechanisms of the impact of stressors on AI adoption intention.

Inconsistencies in the effects of technostress on employees have been identified in previous studies. Some scholars posit that technostress yields positive outcomes, such as increased productivity and innovation,[24,25] while others argue that it may induce negative emotions like anxiety, nervousness, uneasiness, and fatigue. These negative emotions could potentially reduce technology adoption intention or lead to resistance or non-use of new technologies.[26–28] To address this inconsistency, this study employs the Challenge–Hindrance Stressor Framework (CHSF) to categorize stressors into Challenge Stressors and Hindrance Stressors, each with distinct relationships with work outcomes.[29] Challenge stressors promote personal growth and accomplishment, fostering positive job attitudes and behaviors. In contrast, hindrance stressors obstruct achievement, leading to negative work attitudes and behaviors.[30] Following Benlian, this study categorizes technostress into challenge technology stressors (CTS) and hindrance technology stressors (HTS).[31] Identifying the dual nature of technostress will enhance our understanding of its diverse impacts on employees' work attitudes and behaviors.

The existing literature on the adoption of new technology posits that individuals' responses to technology vary widely,[32] a phenomenon attributed to the range of positive and negative emotions triggered by technology.[33] Thus, gaining a better understanding of emotional responses to technology is crucial.[34] This study aims to elucidate the psychological mechanisms through the lens of the Affective Events Theory (AET), a psychological model proposing that work events trigger individual emotional responses, subsequently influencing attitudes and behaviors.[35] The AET is employed in this study to explicate the intricate relationship between emotions, attitudes, and behaviors in work events. Affect serves as a pivotal mechanism linking these events to attitudes and behaviors.[36] Integrating the CHSF, challenge technology stressors, as positive events, stimulate positive affect such as enthusiasm and motivation, thereby promoting behavior. Conversely, hindrance technology stressors, perceived as negative events, elicit negative affect such as exhaustion and anxiety, hindering behavior. Consequently, different stressors induce distinct psychological responses and subsequent behavioral outcomes.[37,38]

In line with the AET, individual characteristics moderate the link between work events and emotional responses, thereby influencing attitudes and behaviors.[35] An essential individual trait in this context is technical self-efficacy, reflecting a person's confidence and ability to perform specific technical tasks.[39] Technical self-efficacy significantly influences individuals' acceptance of new technologies.[21] While the impact of self-efficacy on technology adoption has been explored in the existing literature,[21,35] limited research has focused on AI technology contexts. Technical self-efficacy may serve as one of the boundary conditions indirectly affecting AI adoption intention through different emotional experiences of challenge and hindrance technology stressors.

By elucidating the mediation mechanism and exploring the boundary conditions between AI-driven technology stressors and employees' intention to adopt AI in the workplace, this study makes three notable contributions: 1. Delineating the Dualistic Nature of Technostress: This research underscores the dualistic nature of technostress and its consequential impact on AI adoption intention. It provides valuable insights into the application of the AET in the context of AI adoption. 2. Examining Affective Reaction Processes: The study systematically investigates the distinct affective reaction processes associated with employee AI adoption intention in response to two types of technostress. This examination enhances our understanding of the nuanced psychological mechanisms involved in the adoption of AI technologies. 3. Exploring the

Boundary Condition of Technical Self-Efficacy: This research delves into the boundary condition of technical self-efficacy, contributing to a deeper comprehension of individual differences in the adoption of AI technology. In sum, this study seeks to advance our understanding of the complexities surrounding AI adoption in the workplace, offering valuable insights for both theoretical development and practical implications.

Theoretical Foundation and Research Hypotheses

AI-Driven Challenge and Hindrance Technology Stressors and Affective Reactions

The AET posits that individuals' cognitive appraisal of work events is crucial in determining their affective reactions. Work events can be categorized into two types: uplifting events, which facilitate the achievement of work goals and are associated with positive affect, and hassles or negative events, which hinder the accomplishment of work goals and are associated with negative affect.[40] Individuals generate positive or negative affective reactions based on their evaluation of whether work events promote or hinder the realization of their goal values.[30]

In the context of AI technology in the workplace, various work events are identified as challenge technology stressors, such as the need to acquire new technical skills, utilizing AI technology to handle substantial workloads, managing multitasking and project assignments, and solving complex problems.[31] Conversely, hindrance technology stressors include factors like increased workloads, technical difficulties, conditional limitations, and insufficient resources.[31] The way employees perceive these AI-related technical requirements is crucial. If these requirements are seen as opportunities for personal growth and align with individual goal values, employees are likely to assess them as favorable work events, categorizing them as challenge technology stressors.[41] In turn, this assessment can lead to increased employee initiative, a more positive outlook, heightened work enthusiasm,[42] and the elicitation of positive affective reactions.[43] Thus, a positive cognitive assessment triggered by challenge technology stressors will activate individuals' positive affective reactions.[36] Conversely, if employees perceive that AI technical requirements hinder their career development and goal attainment, they will regard these requirements as unfavorable work events, categorizing them as hindrance technology stressors.[41] This evaluation leads to negative affective reactions, including anxiety, frustration, and depression.[23,24] Negative cognitive evaluations triggered by hindrance technology stressors often result in negative affective responses in individuals,[36] such as AI anxiety.[44,45] AI anxiety refers to the overall affective anxiety or fear that individuals experience towards work and life as a result of the advancement of AI technology.[23,46] This study predicts that AI anxiety is triggered by hindrance technology stressors, negatively affect employees' physical and mental well-being and work life.[47] Therefore, we propose:

H1a: AI-driven challenge technology stressors are positively related to positive affect.

H1b: AI-driven hindrance technology stressors are positively related to AI anxiety.

Affective Reactions and AI Adoption Intention

Technology adoption intention represents individuals' willingness to accept and engage with new technology[14] and significantly predicts actual adoption behavior.[16,32,48] According to the AET, employees' emotional reactions to work events significantly influence their workplace behaviors. Emotions are psychological and experiential states directed towards an object, such as a technology, a person, or an event.[49] Previous research has indicated that employees' reactions to new technology are derived from their emotional experiences with it.[50] Affect is pivotal in individuals' intentions to adopt AI technology.[51,52] Positive emotions tend to enhance positive behaviors, while negative emotions are linked to negative behaviors.[51,53] Positive emotional reactions at work boost a sense of achievement and a willingness to invest more time, effort, and attention to overcome challenges related to AI technology, thus promoting AI adoption.[54] Positive affect, considered a positive psychological resource, can enhance positive work behaviors by augmenting an individual's psychological resources.[55] Conversely, negative emotional reactions, particularly feelings of helplessness and a perceived lack of control or coping mechanisms, lead to avoidance and withdrawal. Negative emotional reactions often manifest as anxiety toward AI technology,[46] reducing the willingness for adoption.[56,57] AI anxiety is considered a significant factor that has a negative impact on an individual's AI adoption intention.[58] Based on the above discussion, this study proposes the following hypotheses:

H2a. Positive affect is positively related to AI adoption intention.

H2b. AI anxiety is negatively related to AI adoption intention.

The Mediating Role of Affective Reactions

The AET posits that work-related events trigger various affective responses. These responses, in turn, significantly influence changes in individual attitudes and behaviors. The affective responses triggered by work stress events directly influence individual behavior, serving as a mediating mechanism through which work stress events impact work behavior.[40] Additionally, the CHSF suggests that distinct stressors elicit different affective and behavioral responses.[59] Research has found that challenge stressors generate positive behaviors in individuals through positive affect, whereas hindrance stressors lead to negative behaviors through negative affect.[38,60] Therefore, it can be inferred that challenge and hindrance technology stressors may have varying effects on AI adoption intention through distinct affective experiences.

To cope with AI-driven technostress, employees assess whether it will bring challenges or hinderances. The intense emotions evoked during the assessment,[61] whether positive or negative, will influence their intention to adopt AI.[51] In the context of AI technology, employees who perceive growth opportunities, value, and challenges brought by the new technology view challenge technology stressors as positive work events. This perception triggers positive affective reactions and motivates employees to actively embrace AI technology, increasing their intention for adoption.[49,52] Conversely, when employees perceive technological complexity, future uncertainty, and the possibility of job displacement, hindrance technology stressors are seen as negative work events. Hindrance technology stressors trigger negative affective experiences, potentially making employees feel incapable of adapting to work changes and controlling their work environment, all of which create a sense of anxiety.[62,63] This anxiety can reduce AI adoption intention.[34] Therefore, based on the logical chain of "affective event - affective response - attitude or behavior" within the framework of affective events, we propose:

H3a: Positive affect mediates the relationship between challenge technology stressors and AI adoption intention.

H3b: AI anxiety mediates the relationship between hindrance technology stressors and AI adoption intention.

The Moderating Role of Technical Self-Efficacy

Technical self-efficacy refers to individuals' personal judgments regarding their knowledge, skills, or abilities required for using technology,[39] which has been identified as an effective mechanism influencing employees' emotional responses in the workplace.[64] According to the AET, employees' technical self-efficacy significantly affects their reactions to AI-related stressors.

On the one hand, when employees with higher technical self-efficacy encounter AI-driven challenge technology stressors, they perceive themselves as more capable of adapting to new AI technological changes.[64] They have greater confidence in learning new technologies and completing work tasks.[65] As a result, they can effectively control and overcome these challenge technology stressors, transforming them into opportunities for self-growth, learning, and personal value.[41] This positive outlook leads to more positive emotional experiences. In other words, the positive relationship between challenge technology stressors and positive emotions is stronger for employees with higher technical self-efficacy. Conversely, employees with lower technical self-efficacy feel less capable of adapting to new AI environments and using AI technologies effectively.[39] They lack confidence in handling these challenges, resulting in fewer positive emotional experiences. On the other hand, employees with higher technical self-efficacy view hindrance technology stressors as obstacles that can be overcome.[65] They effectively manage the detrimental factors, reducing negative emotions such as AI anxiety,[23] which is associated with resistance towards technological change. Essentially, for employees with higher technical self-efficacy, the positive relationship between hindrance technology stressors and negative emotions becomes relatively weak. Conversely, employees with lower technical self-efficacy perceive hindrance technology stressors as beyond their ability to control and cope with.[35] This perception increases their feelings of threat and leads to negative emotions such as insecurity and anxiety. In other words, for employees with lower technical self-efficacy, the positive relationship between hindrance technology stressors and negative emotions is stronger. Thus, we propose:

H4a: Technical self-efficacy moderates the relationship between AI-driven challenge technology stressors and positive affect, such that this relationship will be stronger when technical self-efficacy is high than when it is low.

H4b: Technical self-efficacy moderates the relationship between AI-driven hindrance technology stressors and AI anxiety, such that this relationship will be weaker when technical self-efficacy is high than when it is low.

Based on the above hypotheses of mediation and moderation, we propose the first-stage moderated mediation hypothesis. Technical self-efficacy moderates the relationship between AI-driven technostress and affect, subsequently influencing AI adoption intentions. Specifically, for employees with high technical self-efficacy, the indirect effect of AI-driven challenge technology stressors on AI adoption intentions through positive affect is stronger, and weaker for those with low technical self-efficacy. Conversely, for employees with high technical self-efficacy, the indirect effect of AI-driven hindrance technology stressors on AI adoption intentions through AI anxiety is weaker, and stronger for those with low technical self-efficacy. Thus,

H5a: Technical self-efficacy moderates the mediating relationship of AI-driven challenge technology stressors and AI adoption intention through positive affect, such that the mediated relationship will be stronger when the technical self-efficacy is high than when it is low.

H5b: Technical self-efficacy moderates the mediating relationship of AI-driven hindrance technology stressors and AI adoption intention through AI anxiety, such that the mediated relationship will be weaker when the technical self-efficacy is high than when it is low.

According to the above proposed hypotheses, this study proposes the following research framework (See Figure 1).

Research Method

Study Design

This study adopted a comprehensive approach for data collection, specifically focusing on employees within a broad spectrum of targeting enterprises heavily dependent on AI devices or technologies across diverse regions and industries. The recruitment of participants was facilitated through the utilization of snowball sampling, a method deemed appropriate for the Chinese context.[66]

A total of 400 participants were selected from 11 distinct companies located in Guangdong province, China. The sample participants spanned various sectors, including the information technology industry, financial services industry, education industry, and manufacturing industry. This approach aimed to guarantee a comprehensive and diverse representation of professionals across various fields. Furthermore, to address potential common method bias, the data collection process was structured as a three-wave survey, with each wave conducted at one-month intervals, as recommended by Podsakoff et al.[67] At

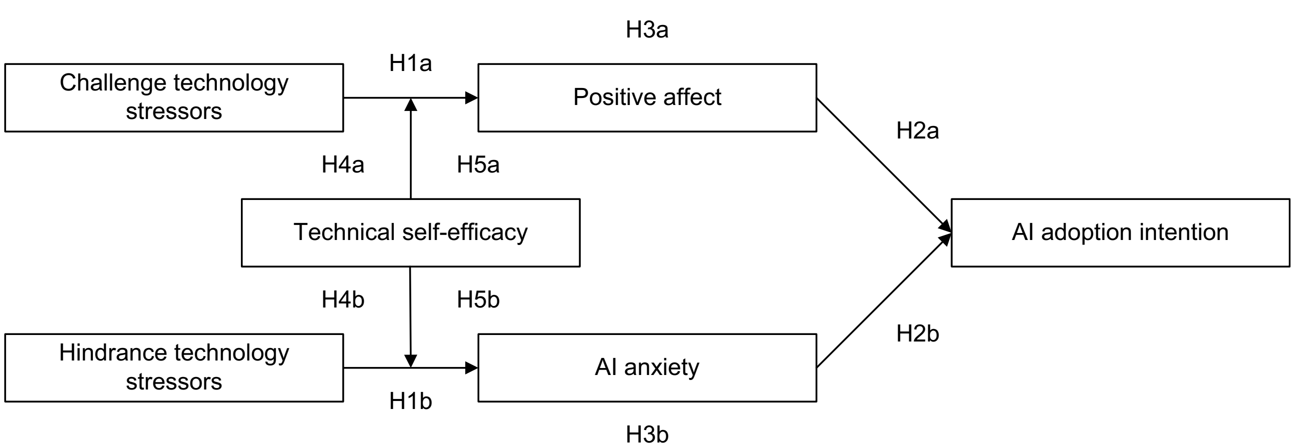

Figure 1 Proposed moderated mediation model.

Time 1, participants provided demographic information and responded to inquiries about AI-driven challenge and hindrance technology stressors. At Time 2, data pertaining to positive affect and AI anxiety were gathered. At Time 3, information regarding technical self-efficacy and AI adoption intention was collected. The questionnaires across three stages were matched using the last four digits of the mobile phone numbers.

The actual process of distributing the questionnaires, we partnered with human resources managers or directors from these companies to distribute the questionnaires. The HR managers/directors randomly selected the employees of various departments to participate in the survey. We employed an online distribution and questionnaire completion method. We explained the academic use of the survey results and assured respondents of the confidentiality of their responses. The entire survey process transpired from January 2023 to April 2023.

Participants

In the survey data collection section, during the first phase, we distributed questionnaires to 400 employees, resulting in a total of 362 valid responses and an effective response rate of 90.5%. One month later, in the second phase of questionnaire collection, we distributed questionnaires to the same 362 employees who participated in the first phase, receiving a total of 333 valid responses and achieving an effective response rate of 92.0%. After another month, in the final phase of questionnaire collection, we distributed questionnaires to the 333 employees who participated in both the first and second phases, obtaining a total of 301 valid responses and maintaining an effective response rate of 90.4%. The reduction in sample size at different stages of data collection was attributed to the unavailability of some participants in the companies during our survey, which could be due to reasons such as sick leave, business trips, and other individual factors.

The descriptive statistics related to the participants in Table 1 reveal that 51.2% were male, while 48.8% were female. In terms of age distribution, the participants comprised 22.6% below the age of 26, 23.9% between the ages of 26 and 30, 20.6% aged 31–35, 16.9% aged 36–40, and 16.0% were above the age of 40. Regarding occupational roles, 37.9% held ordinary positions, 44.9% were designated as frontline workers, and 17.2% occupied middle or senior managerial positions. Regarding educational attainment, 19.6% possessed college degrees or lower, 37.5% held bachelor's degrees, and 42.9% had achieved master's degrees or beyond.

Measures

To ensure the equivalence of measures between the Chinese and English versions, following Brislin's[68] suggestion, we initiated the process by translating the original questionnaire into Chinese. Subsequently, we enlisted the expertise of two bilingual foreign-language experts to perform a back-translation from Chinese to English. The back-translated version was then compared to the original version to identify any discrepancies or differences in meaning. If discrepancies were

Table 1 Characteristics of Participants

Characteristics	Categories	Frequency	Percentage (%)
Gender	Male	154	51.2
	Female	147	48.8
AGE	Below the age of 26	68	22.6
	26–30	72	23.9
	31–35	62	20.6
	36–40	51	16.9
	Above the age of 40	48	16.0
Occupational roles	Ordinary employees	114	37.9
	Frontline workers	135	44.9
	Middle or senior managers	52	17.2
Education	College's degrees or lower	59	19.6
	Bachelor's degrees	113	37.5
	Master's degrees or beyond	129	42.9

found, adjustments were made to the translated version. This iterative process involve multiple rounds of translation and back translation until a satisfactory level of equivalence was achieved.

AI-Driven Challenge and Hindrance Technology Stressors

We employed Benlian's[31] sixteen-item scale to assess AI-driven challenge and hindrance technology stressors. Specifically, eight items were designed to measure challenge technology stressors, and an additional eight items were dedicated to gauging hindrance technology stressors. Sample items include "Complete a lot of work with AI devices or technologies" for challenge technology stressors, and "Encounter major troubles or hassles (e.g., breakdown, crash, malfunctions) with AI devices or technologies" for hindrance technology stressors. Respondents rated all items on a five-point Likert scale, ranging from (1) "never" to (5) "extremely often". The Cronbach's alpha coefficient for challenge technology stressors was 0.96, and for hindrance technology stressors, it was also 0.96.

Positive Affect

We employed Watson's[69] ten-item scale from the PANAS to assess positive affect. Participants were requested to indicate the degree to which they typically experienced different feelings and emotions (e.g., interested, enthusiastic). All items were evaluated using a five-point Likert scale, ranging from (1) "very slightly or not at all" to (5) "extremely". The Cronbach's alpha for this scale was 0.98.

AI Anxiety

We used the Wang and Wang's[23] 21-item scale to measure employees' AI anxiety. A sample item was "I am afraid that an AI technique may replace humans". All items were rated on a five-point Likert scale, ranging from (1) "never" to (5) "very often". The Cronbach's alpha for this scale was 0.98.

Technical Self-Efficacy

We used Turja's[70] three-item scale to measure technical self-efficacy. A sample item was "I'm confident in my ability to learn how to use AI technique if they were to become part of my unit". All items were rated on a five-point Likert scale, ranging from (1) "strongly disagree" to (5) "strongly agree". The Cronbach's alpha for this scale was 0.90.

AI Adoption Intention

We used Karahanna's[71] two-item scale to measure participants' willingness to adopt AI technology in their work. A sample item was "I intend to adopt AI technology in my job within the next months". All items were rated on a five-point Likert scale, ranging from (1) "strongly disagree" to (5) "strongly agree". The Cronbach's alpha for this scale was 0.89.

Control Variables

Building upon insights derived from prior research, which identified associations between gender, age, education, and occupational position with technology adoption intention,[14,16] this study systematically controls for these demographic factors. The prevailing understanding suggests that younger employees tend to manifest a heightened level of AI adoption intention due to their increased openness to novel concepts.[4,17,20] Additionally, an anticipated distinction is made concerning male employees, with the expectation that they will exhibit a more pronounced attitude of acceptance than their female counterparts.[4,17,20] Furthermore, it is commonly posited that employees with higher educational levels are inclined towards a greater acceptance of advanced technological innovations.[72]

Data Analysis

In this study, descriptive statistical analysis, assessment of internal reliability for the scales, and examination of correlations between variables were conducted using SPSS v21.0. Confirmatory factor analysis (CFA) was performed using Mplus 7.0. Additionally, to test our hypotheses, we adopted the PROCESS macro for SPSS, developed by Hayes.[73] This tool offers two key advantages. Firstly, it functions as a path-analytic tool, allowing researchers to simultaneously explore mediation, moderation, and moderated mediation effects. Secondly, it facilitates a direct examination of moderated mediation effects by providing an Index of Moderated Mediation. In hypotheses testing, we selected Model 4 and Model 7 from the Process tool,[73] representing a mediation and a moderated mediation with the first-stage moderation. We employed 5000 bootstraps and a confidence interval (CI) for estimating the corresponding effects.

Results

Confirmatory Method Variance and Discriminant Validity

A Harman's single-factor test was conducted to assess the possibility of common method bias.[67] The analysis revealed that the first factor explained 49.06% of the variance, which fell below the required threshold of 50%. This suggests that common method bias was not a significant concern in this study.

A series of confirmatory factor analyses were performed to examine the discriminant validity of all research variables, and the results of the model fit are presented in Table 2. As indicated in Table 2, the hypothesized six-factor model, which includes challenge and hindrance technology stressors, positive affect, AI anxiety, technical self-efficacy, and AI adoption intention [$\chi2$ (1259) = 2229.81, CFI = 0.95, TLI = 0.94, SRMR = 0.04, and RMSEA = 0.05], fits the data well (i.e., $\chi2/df < 3$, CFI > 0.90, TLI > 0.90, SRMS < 0.08 and RMSEA < 0.08).[74] Furthermore, comparisons of the hypothesized model with all alternative models using chi-square difference tests revealed that the hypothesized model provides the best fit to the data, thereby supporting the discriminability of the measures.

Descriptive Statistics and Correlations

Table 3 depicts the descriptive statistics and bivariate correlations among the study variables. The findings revealed a positive correlation between challenge technology stressors and positive affect ($r=0.59$, $p<0.001$). Additionally, hindrance technology stressors exhibited a positive association with artificial intelligence anxiety ($r=0.55$, $p<0.001$). Furthermore, the results indicated a positive relationship between positive affect and AI adoption intention ($r=0.56$, $p<0.001$), whereas AI

Table 2 The Results of Confirmatory Factor Analyses

Measurement Model	χ^2	df	χ^2/df	CFI	TLI	SRMR	RMSEA
Six-factor model	2229.81	1259	1.77	0.95	0.94	0.04	0.05
Five-factor model	2702.63	1264	2.14	0.92	0.92	0.12	0.06
Four-factor model	4488.30	1268	3.54	0.82	0.82	0.14	0.09
Three-factor model	7358.06	1271	5.78	0.67	0.65	0.18	0.13
Two-factor model	9072.86	1273	7.13	0.57	0.55	0.18	0.14
One-factor model	9397.50	1274	7.38	0.55	0.54	0.14	0.15

Note: N=301.
Abbreviations: CFI, Comparative Fit Index (cutoff value, 0.90); TLI, Tucker-Lewis Index (cutoff value, 0.90); SRMR, Standardized Root Mean square (cutoff value, 0.05); RMSEA, Root Mean Square of Approximation (cutoff value, 0.06).

Table 3 Descriptive Statistics and Correlations

Variables	M	SD	1	2	3	4	5	6	7	8	9
1. Gender	0.51	0.50									
2. Age	2.80	1.38	0.06								
3. Position	1.79	0.72	0.23***	0.58***							
4. Education	2.23	0.76	0.13*	0.51***	0.60***						
5. CTS	3.26	1.09	0.23***	0.09	0.20***	0.30***					
6. HTS	3.11	1.02	−0.17**	−0.12*	−0.23***	−0.28***	−0.53***				
7. Positive affect	3.33	1.17	0.14*	0.09	0.20***	0.35***	0.59***	−0.55***			
8. AI anxiety	3.01	1.11	−0.20**	−0.04	−0.22***	−0.34***	−0.55***	0.55***	−0.58***		
9. Technical self-efficacy	2.88	0.80	0.05	−0.05	0.01	0.03	0.47***	−0.02	0.40***	−0.04	
10. AI adoption intention	3.31	1.10	0.21***	0.13*	0.24***	0.28***	0.53***	−0.53***	0.56***	−0.53***	0.10

Notes: N = 301; *p < 0.05, **p < 0.01, ***p < 0.001.
Abbreviations: CTS, challenge technology stressors; HTS, hindrance technology stressors.

anxiety displayed a negative correlation with AI adoption intention (r=−0.53, p<0.001). These results provide initial support for Hypotheses 1a, 1b, 2a, 2b.

Hypotheses Testing

Regarding Hypotheses 1a and 1b, we predicted a positive relationship between challenge technology stressors and positive affect and a positive relationship between hindrance technology stressors and AI anxiety. As presented in Table 4 (M1-2, M2-2), statistical results revealed significant positive relationships between challenge technology stressors and positive affect (B=0.56, p<0.001), and between hindrance technology stressors and AI anxiety (B=0.52, p<0.001). Therefore, Hypotheses 1a and 1b were supported. Moving on to Hypotheses 2a and 2b, we anticipated a positive relationship between positive affect and AI adoption intention, and a negative relationship between AI anxiety and AI adoption intention. Statistical results (Table 4, M1-3, M2-3) unveiled a significant positive relationship between positive affect and AI adoption intention (B=0.49, p<0.001), and a significant negative relationship between hindrance technology stressors and AI anxiety (B=−0.48, p<0.001). Therefore, Hypotheses 2a and 2b were supported. H3a and H3b posited that positive affect mediates the relationship between challenge technology stressors and AI adoption intention, while AI anxiety mediates the relationship between hindrance technology stressors and AI adoption intention, respectively. To examine these mediation effects, we adhered to Hayes'[73] procedure. After accounting for positive affect, the effect of challenge technology stressors on AI adoption intention remained significant (B=0.29, p<0.001), implying partial mediation. Similarly, after accounting for AI anxiety, the effect of hindrance technology stressors on AI adoption intention remained significant (B=−0.34, p<0.001), signifying partial mediation. The bootstrapping results also validated the significance of the indirect effects (95% CI [0.10, 0.31]; 95% CI [−0.29, −0.08]), respectively. Thus, Hypotheses 3a and 3b received support.

Hypotheses 4a and 4b predicted that technical self-efficacy moderates the relationship between challenge technology stressors and positive affect, as well as the relationship between hindrance technology stressors and AI anxiety, respectively. As shown in Table 5, we observed a significant interaction between challenge technology stressors and technical self-efficacy in predicting positive affect (B= 0.51, p< 0.001). Similarly, there was a significant interaction between hindrance technology stressors and technical self-efficacy in predicting AI anxiety (B=−0.37, p<0.001). Figures 2 and 3 display the interaction plot based on values plus and minus one standard deviation from the mean of technical self-efficacy. Figure 2 illustrates that the positive relationship between AI-driven challenge technology stressors and positive affect is more pronounced among individuals with high technical self-efficacy than those with low technical self-

Table 4 Regression Results for Mediation Model

Variables	M1-1 X1→Y	M1-2 X1→M1	M1-3 M1→Y	M1-4 X→M1→Y	M2-1 X2→Y	M2-2 X2→M2	M2-3 M2→Y	M2-4 X2→M2→Y
Constant	1.21***	0.89***	1.23***	0.90***	4.31***	2.06***	4.25***	4.97***
Gender	0.16	−0.01	0.25*	0.16	0.23*	−0.18	0.21	0.17
Age	−0.00	−0.06	0.01	0.02	−0.02	0.14**	0.04	0.03
Position	0.13	0.01	0.13	0.12	0.08	−0.06	0.08	0.06
Education	0.11	0.35***	0.03	−0.01	0.16	−0.38***	0.06	0.04
CTS	0.48***	0.56***		0.29***				
HTS					−0.51***	0.52***		−0.34***
Positive affect			0.49***	0.34***				
AI anxiety							−0.48***	−0.32***
Effect	**Bootstrap results for indirect effect**				**Bootstrap results for indirect effect**			
	M	**SE**	**LLCI**	**ULCI**	**M**	**SE**	**LLCI**	**ULCI**
	0.20	0.06	0.10	0.31	−0.17	0.05	−0.29	−0.08

Notes: N=301. Unstandardized regression coefficients are reported. Bootstrap sample size=5000. *p < 0.05; **p < 0.01;***p < 0.001.
Abbreviations: CTS, challenge technology stressors; HTS, hindrance technology stressors; LL, lower limit; UL, upper limit; CI, confidence interval.

Table 5 Regression Results for Moderation and Moderated Mediation Model

Predictor	Positive Affect				AI Anxiety			
	B	SE	t	p	B	SE	t	p
Moderation model								
Constant	2.77	0.15	18.20	<0.001	3.43	0.16	20.91	<0.001
Gender	−0.09	0.09	−0.96	>0.05	−0.16	0.10	−1.68	>0.05
Age	−0.03	0.04	−0.69	>0.05	0.11	0.04	2.62	<0.01
Position	−0.00	0.08	−0.04	>0.05	0.05	0.09	0.51	>0.05
Education	0.22	0.08	2.80	<0.01	−0.33	0.08	−4.08	<0.001
CTS	0.74	0.05	13.71	<0.001				
HTS					0.46	0.05	9.50	<0.001
Technical self-efficacy	0.10	0.06	1.66	>0.05	−0.19	0.06	−3.06	<0.01
CTS × Technical self-efficacy	0.51	0.04	11.87	<0.001				
HTS × Technical self-efficacy					−0.37	0.05	−7.82	<0.001
Moderated mediation model								
Technical self-efficacy	indirect effect	Boot SE	Boot LLCI	Boot ULCI	indirect effect	Boot SE	Boot LLCI	Boot ULCI
Index of moderated mediation	0.18	0.05	0.08	0.29	0.12	0.05	0.04	0.22
Conditional indirect effect at Technical self-efficacy = M ± 1 SD								
M-1SD	0.11	0.05	0.04	0.23	−0.24	0.08	−0.41	−0.12
M+1SD	0.40	0.12	0.20	0.65	−0.05	0.04	−0.14	0.02

Note: N=301. Bootstrap sample size=5000.
Abbreviations: CTS, challenge technology stressors; HTS, hindrance technology stressors; LL, lower limit; UL, upper limit; CI, confidence interval.

efficacy. In contrast, Figure 3 demonstrates that the positive relationship between AI-driven hindrance technology stressors and AI anxiety is less prominent among individuals with high technical self-efficacy when compared to those with low technical self-efficacy. Thus, Hypotheses 4a and 4b were supported.

As indicated in Table 5, the indices of moderated mediation were found to be significant: Boot indirect effect = 0.18, Boot SE = 0.05, Boot LLCI = 0.08, Boot ULCI = 0.29 (with positive affect as a mediator); Boot indirect effect = 0.12,

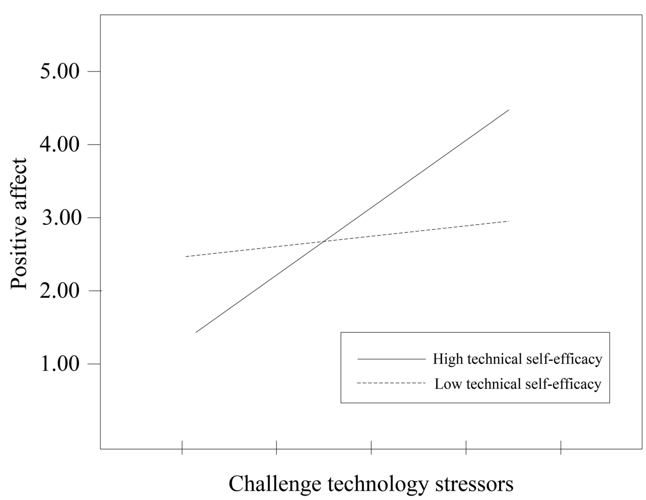

Figure 2 Moderating effect of technical self-efficacy on the relationship between challenge technology stressors and positive affect.

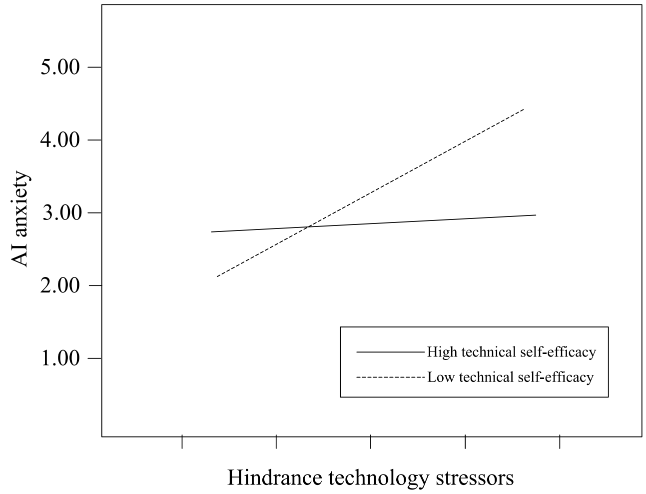

Figure 3 Moderating effect of technical self-efficacy on the relationship between hindrance technology stressors and AI anxiety.

Boot SE = 0.05, Boot LLCI = 0.04, Boot ULCI = 0.22 (with AI anxiety as a mediator). This lends support to Hypotheses 5a and 5b.

Discussion

By incorporating the Affective Events Theory and the Challenge-Hindrance Stressor Framework, this study explored how and when AI-driven challenge and hindrance technology stressors influence AI adoption intention. This study yields two major research findings. First, challenge technology stressors enhance employees' AI adoption intention by triggering positive affect, while hinderance technology stressors reduce AI adoption intention by eliciting AI anxiety. Employees' emotional reactions to AI-driven technostress are crucial for their AI adoption intention. Second, technical self-efficacy amplifies the positive effect of challenge technology stressors while diminishes the negative effect of hindrance technology stressors, on affective reactions and subsequent AI adoption intention. This finding suggests that employees' confidence in their knowledge, skills, or abilities to use AI technology help them to cope with the technostress and uncertainty associated with AI. This study provides insights for future studies and practices aimed at better understanding employees' emotional states in the context of AI-driven challenges and hindrances, with the goal of improving their willingness to adopt technology and promoting both their professional development and organizational innovation.

Theoretical Implications

The study contributes to the theory in the following three aspects:

First, the current study enriches the existing literature on AI technology adoption by unraveling the antecedent variable of technostress. Previous research on whether technostress is beneficial or detrimental to employees has produced inconsistent results. This study investigates the dualistic nature of technostress, distinguishing challenge and hindrance technostress in the context of AI applications, to deepen the understanding of employees' AI adoption intention.

Second, this study, based on the AET, reveals the psychological mechanisms through which challenge and hindrance technology stressors influence AI technology adoption by introducing positive and negative emotions as crucial mediating variables. The results indicate that AI-driven challenge and hindrance technology stressors have different effects on AI adoption intention through different emotional responses, adding insights into the existing literature. This study extends the application of the Affective Events Theory to the research on AI technology adoption, supplementing previous theories.

Third, this study enhances our understanding of individual differences in the relationship between technostress and technology adoption by examining the moderation effects of technical self-efficacy. Technical self-efficacy serves as a personal resource for coping with technostress and plays a pivotal role in stress management within the workplace. This study reveals how technical self-efficacy moderates the impact of AI-driven technostress on technology adoption through emotional reactions, providing valuable supplementation to the study of AI technology applications.

Practical Implications

Employees' willingness to adopt AI technologies is critical for driving effective technological transformation within organizations. The research findings underscore three practical implications with significant emphasis. First, managers must address AI-driven technostress in the workplace, recognizing its dualistic impact. When viewed as a challenge, technostress positively influences AI adoption by fostering positive emotions. Conversely, when perceived as a hindrance, it hampers AI adoption due to the emergence of AI anxiety. To navigate this dualistic impact, organizations should implement intelligent workflows, offer technical support, and empower employees with autonomy and involvement.[75] Aligning job skills with personal growth enhances understanding and adaptation to evolving AI technologies.[7] Additionally, an effective organizational support system is crucial.[76] Framing AI technostress as a challenge encourages intentional AI adoption, fostering a positive environment for both professional development and personal goals.

Second, organizations should pay attention to employees' emotional reactions to AI technology. On the one hand, organizations should take measures to help employees perceive AI technology as a challenge to stimulate employees' positive emotions. For example, organizations can enhance employees' understanding and involvement of AI technology through communication, explanation, and feedback, and increase their identification and belonging.[9,77] For employees who cope well with AI challenges, organizations should reward and praise them, and ignite their enthusiasm, proactiveness, and innovation, and promote their AI adoption.[10] On the other hand, to curb AI anxiety, organizations should evaluate and intervene in negative emotional reactions,[78] and prevent mental health risks.[34] For example, organizations can offer psychological counseling and support to employees through assistance and mentoring programs, and help them adapt to the work changes, and protect their mental health.[79] The assistance and mentoring programs provide employees with emotional support, feedback, and guidance, and improve their self-efficacy and motivation in using AI technology.[80,81] These interventions are valuable for employees to overcome negative emotions toward AI technology, improving their AI adoption intention.

Last but not least, organizations should take employees' individual differences into account, design and implement targeted training and support programs that align with their personalized needs and skill levels. These efforts contribute to enhancing individual technical self-efficacy, promoting employees' AI technology adoption intention, and strengthening the organization's overall technological transformation and innovative capabilities.

Limitation and Future Research

Three limitations of this study need to be mentioned. First, all variables in our research were based on self-reporting, potentially resulting in common method variance. Although this study has partially addressed this concern by employing a three-wave data collection process and conducting Harman's single-factor test for post hoc verification, future research could further mitigate the common method variance issue by incorporating multi-source responses. For instance, using supervisor assessments instead of self-reported questionnaires to evaluate employees' AI adoption behavior would minimize the potential impact of common method variance. Second, the current measurement of affect overlooks the dynamic and complex nature of daily fluctuations in employees' emotions caused by technology-related stress. This limitation may lead to an incomplete understanding of how technostress affects employees' emotions over time. Future research conducting longitudinal daily surveys on technology-related stress to assess its evolving emotional impact is necessary. Third, the study only examines the individual level boundary factor of technical self-efficacy. Future studies that identify other contextual boundary factors, such as digital leadership and innovation climate, comprehend our understanding of AI adoption intention.

Conclusion

This study investigates how and when AI-driven challenge and hindrance technology stressors influence AI adoption intention. Research findings indicate that different types of AI-driven technostress trigger distinct affective reactions to influence employees' willingness to adopt AI technology. Positive affect mediates the positive relationship between challenge technology stressors and AI adoption intention, while AI anxiety mediates the negative relationship between hindrance technology stressors and AI adoption intention. Furthermore, technical self-efficacy moderates the impact of

AI-driven technostress on affective responses. Specifically, high technical self-efficacy strengthens the relationship between AI-driven challenge technology stressors and positive affect, while weakening the connection between AI-driven hindrance technology stressors and AI anxiety.

Ethics Statement

All procedures of this research were conducted in accordance with the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards. Before conducting this study, the proposals and ethical standards were reviewed and approved by the academic committee of Macau University of Science and Technology (Approval number: MSB-20231212). Moreover, we formally introduced to all participants important information about this study and obtained their consent before they participated in the research. Finally, all participant information is anonymous and confidential.

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Disclosure

The authors declare no conflicts of interest in relation to this work.

References

1. Haenlein M, Kaplan A. A brief history of artificial intelligence: on the past, present, and future of artificial intelligence. *Calif Manage Rev*. 2019;61(4):5–14. doi:10.1177/0008125619864925
2. Duan Y, Edwards JS, Dwivedi YK. Artificial intelligence for decision making in the era of big data – evolution, challenges and research agenda. *Int J Inf Manag*. 2019;48:63–71. doi:10.1016/j.ijinfomgt.2019.01.021
3. Paschen J, Wilson M, Ferreira JJ. Collaborative intelligence: how human and artificial intelligence create value along the B2B sales funnel. *Bus Horiz*. 2020;63(3):403–414. doi:10.1016/j.bushor.2020.01.003
4. Belanche D, Casaló LV, Flavián C. Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. *Ind Manag Data Syst*. 2019;119(7):1411–1430. doi:10.1108/IMDS-08-2018-0368
5. Joehnk J, Weissert M, Wyrtki K. Ready or not, AI comes- An interview study of organizational AI readiness factors. *Bus Inf Syst Eng*. 2021;63(1):5–20. doi:10.1007/s12599-020-00676-7
6. Nam K, Dutt CS, Chathoth P, Daghfous A, Khan MS. The adoption of artificial intelligence and robotics in the hotel industry: prospects and challenges. *Electron Mark*. 2021;31(3):553–574. doi:10.1007/s12525-020-00442-3
7. Mingotto E, Montaguti F, Tamma M. Challenges in re-designing operations and jobs to embody AI and robotics in services. Findings from a case in the hospitality industry. *Electron Mark*. 2021;31(3):493–510. doi:10.1007/s12525-020-00439-y
8. Lakshmi V, Bahli B. Understanding the robotization landscape transformation: a centering resonance analysis. *J Innov Knowl*. 2020;5(1):59–67. doi:10.1016/j.jik.2019.01.005
9. Braganza A, Chen W, Canhoto A, Sap S. Productive employment and decent work: the impact of AI adoption on psychological contracts, job engagement and employee trust. *J Bus Res*. 2021;131:485–494. doi:10.1016/j.jbusres.2020.08.018
10. Cheng B, Lin H, Kong Y. Challenge or hindrance? How and when organizational artificial intelligence adoption influences employee job crafting. *J Bus Res*. 2023;164:113987. doi:10.1016/j.jbusres.2023.113987
11. Ghosh B, Daugherty PR, Wilson HJ, Burden A. Taking a systems approach to adopting AI. *Harv Bus Rev*. 2019;2019:1.
12. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q*. 1989;13(3):319–340. doi:10.2307/249008
13. Tornatzky LG, Fleischer M, Chakrabarti AK. *The Processes of Technological Innovation*. Lexington Books; 1990.
14. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: toward a unified view. *MIS Q*. 2003;27(3):425–478. doi:10.2307/30036540
15. Pan Y, Froese F, Liu N, Hu Y, Ye M. The adoption of artificial intelligence in employee recruitment: the influence of contextual factors. *Int J Hum Resour Manag*. 2022;33(6):1125–1147. doi:10.1080/09585192.2021.1879206
16. Sohn K, Kwon O. Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products. *Telemat Inform*. 2020;47:101324. doi:10.1016/j.tele.2019.101324
17. Flavián C, Pérez-Rueda A, Belanche D, Casaló LV. Intention to use analytical artificial intelligence (AI) in services–the effect of technology readiness and awareness. *J Serv Manag*. 2022;33(2):293–320. doi:10.1108/JOSM-10-2020-0378
18. Liu M, Wu J, Zhu C, Hu K. Factors influencing the acceptance of robo-taxi services in China: an extended technology acceptance model analysis. *J Adv Transp*. 2022;2022:8461212. doi:10.1155/2022/8461212

19. Moussawi S, Koufaris M, Benbunan-Fich R. How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents. *Electron Mark*. 2021;31(2):343–364. doi:10.1007/s12525-020-00411-w
20. Chen J, Li R, Gan M, Fu Z, Yuan F. Public acceptance of driverless buses in China: an empirical analysis based on an extended UTAUT model. *Discrete Dyn Nat Soc*. 2020;2020:4318182. doi:10.1155/2020/4318182
21. Cao D, Sun Y, Goh E, Wang R, Kuiavska K. Adoption of smart voice assistants technology among Airbnb guests: a revised self-efficacy-based value adoption model (SVAM). *Int J Hosp Manag*. 2022;101:103124. doi:10.1016/j.ijhm.2021.103124
22. Yam KC, Tang PM, Jackson JC, Su R, Gray K. The rise of robots increases job insecurity and maladaptive workplace behaviors: multimethod evidence. *J Appl Psychol*. 2023;108(5):850–870. doi:10.1037/apl0001045
23. Wang YY, Wang YS. Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior. *Interact Learn Environ*. 2022;30(4):619–634. doi:10.1080/10494820.2019.1674887
24. Tarafdar M, Pullins E, Ragu-Nathan TS. Technostress: negative effect on performance and possible mitigations. *Inf Syst J*. 2015;25(2):103–132. doi:10.1111/isj.12042
25. Saleem F, Malik MI, Qureshi SS, Farid MF, Qamar S. Technostress and employee performance nexus during COVID-19: training and creative self-efficacy as moderators. *Front Psychol*. 2021;12:595119. doi:10.3389/fpsyg.2021.595119
26. Salanova M, Llorens S, Cifre E. The dark side of technologies: technostress among users of information and communication technologies. *Int J Psychol*. 2013;48(3):422–436. doi:10.1080/00207594.2012.680460
27. Chen L, Muthitacharoen A. An empirical investigation of the consequences of technostress: evidence from China. *Inf Resour Manag J*. 2016;29(2):14–36. doi:10.4018/IRMJ.2016040102
28. Feng W, Tu R, Lu T, Zhou Z. Understanding forced adoption of self-service technology: the impacts of users' psychological reactance. *Behav Inf Technol*. 2019;38(8):820–832. doi:10.1080/0144929X.2018.1557745
29. Cavanaugh MA, Boswell WR, Roehling MV, Boudreau JW. An empirical examination of self-reported work stress among U.S. managers. *J Appl Psychol*. 2000;85(1):65–74. doi:10.1037/0021-9010.85.1.65
30. LePine MA. The challenge-hindrance stressor framework: an integrative conceptual review and path forward. *Group Organ Manag*. 2022;47(2):223–254. doi:10.1177/10596011221079970
31. Benlian A. A daily field investigation of technology-driven spillovers from work to home. *MIS Q*. 2020;44(3):1259–1300. doi:10.25300/MISQ/2020/14911/
32. Yu X, Xu S, Ashton M. Antecedents and outcomes of artificial intelligence adoption and application in the workplace: the socio-technical system theory perspective. *Inf Technol People*. 2023;36(1):454–474. doi:10.1108/ITP-04-2021-0254
33. Parasuraman A, Colby CL. An updated and streamlined technology readiness index: TRI 2.0. *J Serv Res*. 2015;18(1):59–74. doi:10.1177/1094670514539730
34. Agogo D, Hess TJ. "How does tech make you feel?" a review and examination of negative affective responses to technology use. *Eur J Inf Syst*. 2018;27(5):570–599. doi:10.1080/0960085X.2018.1435230
35. Lazarus RS. Progress on a cognitive-motivational-relational theory of emotion. *Am Psychol*. 1991;46(8):819–834. doi:10.1037/0003-066X.46.8.819
36. Li Z, He B, Sun X. Does work stressors lead to abusive supervision? A study of differentiated effects of challenge and hindrance stressors. *Psychol Res Behav Manag*. 2020;13:573–588. doi:10.2147/PRBM.S249071
37. Rodell JB, Judge TA. Can "good" stressors spark "bad" behaviors? The mediating role of emotions in links of challenge and hindrance stressors with citizenship and counterproductive behaviors. *J Appl Psychol*. 2009;94(6):1438–1451. doi:10.1037/a0016752
38. Tarafdar M, Bolman Pullins E, Ragu-Nathan TS. Examining impacts of technostress on the professional salesperson's behavioural performance. *J Pers Sell Sales Manag*. 2014;34(1):51–69. doi:10.1080/08853134.2013.870184
39. Compeau DR, Higgins CA. Computer self-efficacy: development of a measure and initial test. *MIS Q*. 1995;19(2):189–211. doi:10.2307/249688
40. Weiss HM, Cropanzano R. Affective events theory: a theoretical discussion of the structure, causes and consequences of affective experiences at work. In: Staw BM, Cummings LL, editors. *Research in Organizational Behavior*. Jai Press Inc; 1996:1–74. https://www.webofscience.com/wos/woscc/summary/b7b37b1a-ffb0-4c3e-a2ff-001699cc6b82-bd627a16/relevance/1. Accessed January 23, 2024.
41. Maier C, Laumer S, Tarafdar M, et al. Challenge and hindrance IS use stressors and appraisals: explaining contrarian associations in post-acceptance IS use behavior. *J Assoc Inf Syst*. 2021;22(6):1590–1624. doi:10.17705/1jais.00709
42. Wood SJ, Michaelides G. Challenge and hindrance stressors and wellbeing-based work–nonwork interference: a diary study of portfolio workers. *Hum Relat*. 2016;69(1):111–138. doi:10.1177/0018726715580866
43. LePine MA, Zhang Y, Crawford ER, Rich BL. Turning their pain to gain: charismatic leader influence on follower stress appraisal and job performance. *Acad Manage J*. 2016;59(3):1036–1059. doi:10.5465/amj.2013.0778
44. Johnson DG, Verdicchio M. AI anxiety. *J Assoc Inf Sci Technol*. 2017;68(9):2267–2270. doi:10.1002/asi.23867
45. Georgieff A, Hyee R. Artificial intelligence and employment: new cross-country evidence. *Front Artif Intell*. 2022;5. doi:10.3389/frai.2022.832736
46. Li J, Huang JS. Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. *Technol Soc*. 2020;63:101410. doi:10.1016/j.techsoc.2020.101410
47. Bondanini G, Giorgi G, Ariza-Montes A, Vega-Muñoz A, Andreucci-Annunziata P. Technostress dark side of technology in the workplace: a scientometric analysis. *Int J Environ Res Public Health*. 2020;17(21):8013. doi:10.3390/ijerph17218013
48. Sahu AK, Padhy RK, Dhir A. Envisioning the future of behavioral decision-making: a systematic literature review of behavioral reasoning theory. *Australas Mark J*. 2020;28(4):145–159. doi:10.1016/j.ausmj.2020.05.001
49. Gkinko L, Elbanna A. Hope, tolerance and empathy: employees' emotions when using an AI-enabled chatbot in a digitalised workplace. *Inf Technol People*. 2022;35(6):1714–1743. doi:10.1108/ITP-04-2021-0328
50. Stam KR, Stanton JM. Events, emotions, and technology: examining acceptance of workplace technology changes. *Inf Technol People*. 2010;23(1):23–53. doi:10.1108/09593841011022537
51. Chiu YT, Zhu YQ, Corbett J. In the hearts and minds of employees: a model of pre-adoptive appraisal toward artificial intelligence in organizations. *Int J Inf Manag*. 2021;60:102379. doi:10.1016/j.ijinfomgt.2021.102379
52. Gursoy D, Chi OH, Lu L, Nunkoo R. Consumers acceptance of artificially intelligent (AI) device use in service delivery. *Int J Inf Manag*. 2019;49:157–169. doi:10.1016/j.ijinfomgt.2019.03.008
53. Ding Y. Modelling continued use of information systems from a forward-looking perspective: antecedents and consequences of hope and anticipated regret. *Inf Manage*. 2018;55(4):461–471. doi:10.1016/j.im.2017.11.001

54. Chatterjee S, Bhattacharjee KK. Adoption of artificial intelligence in higher education: a quantitative analysis using structural equation modelling. *Educ Inf Technol*. 2020;25(5):3443–3463. doi:10.1007/s10639-020-10159-7
55. Fredrickson BL. The role of positive emotions in positive psychology: the broaden-and-build theory of positive emotions. *Am Psychol*. 2001;56(3):218–226. doi:10.1037/0003-066X.56.3.218
56. Huang MH, Rust RT. Artificial Intelligence in Service. *J Serv Res*. 2018;21(2):155–172. doi:10.1177/1094670517752459
57. Evanschitzky H, Iyer GR, Pillai KG, Kenning P, Schuete R. Consumer trial, continuous use, and economic benefits of a retail service innovation: the case of the personal shopping assistant. *J Prod Innov Manag*. 2015;32(3):459–475. doi:10.1111/jpim.12241
58. Kaya F, Aydin F, Schepman A, Rodway P, Yetisensoy O, Kaya MD. The roles of personality traits, AI anxiety, and demographic factors in attitudes toward artificial intelligence. *Int J Hum-Comput Interact*. 2022. doi:10.1080/10447318.2022.2151730
59. Horan KA, Nakahara WH, DiStaso MJ, Jex SM. A review of the challenge-hindrance stress model: recent advances, expanded paradigms, and recommendations for future research. *Front Psychol*. 2020;11:560346. doi:10.3389/fpsyg.2020.560346
60. Yang Y, Li X. The impact of challenge and hindrance stressors on thriving at work double mediation based on affect and motivation. *Front Psychol*. 2021;12:613871. doi:10.3389/fpsyg.2021.613871
61. Huang MH, Rust RT. A strategic framework for artificial intelligence in marketing. *J Acad Marking Sci*. 2021;49(1):30–50. doi:10.1007/s11747-020-00749-9
62. McClure PK. "You're Fired", says the robot: the rise of automation in the workplace, technophobes, and fears of unemployment. *Soc Sci Comput Rev*. 2018;36(2):139–156. doi:10.1177/0894439317698637
63. Brougham D, Haar J. Smart technology, artificial intelligence, robotics, and algorithms (STARA): employees' perceptions of our future workplace. *J Manag Organ*. 2018;24(2):239–257. doi:10.1017/jmo.2016.55
64. Bandura A. Self-efficacy mechanism in human agency. *Am Psychol*. 1982;37(2):122–147. doi:10.1037/0003-066X.37.2.122
65. Kim DG, Lee CW. Exploring the roles of self-efficacy and technical support in the relationship between techno-stress and counter-productivity. *Sustainability*. 2021;13(8):4349. doi:10.3390/su13084349
66. Sun LY, Aryee S, Law KS. High-performance human resource practices, citizenship behavior, and organizational performance: a relational perspective. *Acad Manage J*. 2007;50(3):558–577. doi:10.5465/amj.2007.25525821
67. Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP. Common method biases in behavioral research: a critical review of the literature and recommended remedies. *J Appl Psychol*. 2003;88(5):879–903. doi:10.1037/0021-9010.88.5.879
68. Brislin RW. Translation and content analysis of oral and written materials. *Methodology*. 1980;1980:389–444.
69. Watson D, Clark LA, Tellegen A. Development and validation of brief measures of positive and negative affect: the PANAS scales. *J Pers Soc Psychol*. 1988;54(6):1063–1070. doi:10.1037/0022-3514.54.6.1063
70. Turja T, Rantanen T, Oksanen A. Robot use self-efficacy in healthcare work (RUSH): development and validation of a new measure. *AI Soc*. 2019;34(1):137–143. doi:10.1007/s00146-017-0751-2
71. Karahanna E, Straub D, Chervany N. Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Q Manag Inf Syst*. 1999;23(2):183–213. doi:10.2307/249751
72. Yi M, Choi H. What drives the acceptance of AI technology?: the role of expectations and experiences. *arXiv preprint arXiv*. 2023;16:1. doi:10.48550/arXiv.2306.13670
73. Hayes AF. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. Guilford Press; 2013.
74. Kyndt E, Onghena P. The Integration of Work and Learning: tackling the Complexity with Structural Equation Modelling. In: Harteis C, Rausch A, Seifried J editors. *Discourses on Professional Learning*. Professional and Practice-based Learning. Springer Netherlands; 2014:255–291. doi:10.1007/978-94-007-7012-6_14
75. Li JJ, Bonn MA, Ye BH. Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: the moderating roles of perceived organizational support and competitive psychological climate. *Tour Manag*. 2019;73:172–181. doi:10.1016/j.tourman.2019.02.006
76. Duke AB, Goodman JM, Treadway DC, Breland JW. Perceived organizational support as a moderator of emotional labor/outcomes relationships. *J Appl Soc Psychol*. 2009;39(5):1013–1034. doi:10.1111/j.1559-1816.2009.00470.x
77. Chowdhury S, Dey P, Joel-Edgar S, et al. Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Hum Resour Manag Rev*. 2023;33(1):100899. doi:10.1016/j.hrmr.2022.100899
78. Nastjuk I, Trang S, Grummeck-Braamt JV, Adam MTP, Tarafdar M. Integrating and synthesising technostress research: a meta-analysis on technostress creators, outcomes, and IS usage contexts. *Eur J Inf Syst*. 2023;1–22. doi:10.1080/0960085X.2022.2154712
79. Wei W, Li L. The impact of artificial intelligence on the mental health of manufacturing workers: the mediating role of overtime work and the work environment. *Front Public Health*. 2022;10:862407. doi:10.3389/fpubh.2022.862407
80. Gagné M, Parent-Rocheleau X, Bujold A, Gaudet MC, Lirio P. How algorithmic management influences worker motivation: a Self-Determination Theory perspective. *Can Psychol*. 2022;63(2):247–260. doi:10.1037/cap0000324
81. Chang PC, Guo Y, Cai Q, Guo H. Proactive career orientation and subjective career success: a perspective of career construction theory. *Behav Sci*. 2023;13(6):503. doi:10.3390/bs13060503