



The impact of digital stress on work engagement in aging employees: The roles of workplace anxiety and algorithmic competency

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Abstract: This study explores the impact of digital stress on work engagement among 305 aging employees, employing the Job Demands-Resources (JD-R) model as the theoretical framework. It examines the mediating role of workplace anxiety and the moderating effect of algorithmic competency. Data were collected across three time points, with participants completing surveys. Findings reveal that digital stress significantly affects workplace anxiety, which mediates the relationship between digital stress and work engagement. Furthermore, algorithmic competency moderates both the direct relationship between digital stress and workplace anxiety and the indirect effect of digital stress on work engagement through workplace anxiety. Our findings highlight the critical roles of workplace anxiety and algorithmic competency in mitigating the detrimental effects of digital stress on work engagement among aging employees, and offer valuable implications for designing targeted workplace interventions and training programs to enhance digital competency and support employee well-being.

Keywords: aging; digital stress; algorithmic competency; workplace anxiety; work engagement

Introduction

As the global trend of population and workforce aging intensifies, effectively developing and utilizing the human resource potential of aging employees has become a critical issue for addressing demographic shifts (Bai & Lei, 2020), optimizing human resource allocation (Li et al., 2025a), and fostering sustainable economic development (Chand & Tung, 2014). In today's rapidly evolving digital workplace, aging employees—often defined as those aged 45 and above (Billett et al., 2011; Kulik et al., 2016; Zhou et al., 2024)—face unique challenges in adapting to advanced technologies and artificial intelligence, which can lead to digital stress (Funke et al., 2026; Low et al., 2025), a state of psychological strain stemming from the demands of digital tools and systems (Tarafdar et al., 2019). Digital stress can undermine work engagement, a positive, fulfilling work-related state characterized by vigor, dedication, and absorption, which is essential for employee well-being and organizational performance (Schaufeli et al., 2002). Aging employees may be particularly vulnerable to digital stress due to factors such as technological unfamiliarity or perceived obsolescence, potentially diminishing their engagement and productivity (Czaja et al., 2018). Despite the expanding literature on digital stress, its effects on aging employees remain underexplored. Understanding this demographic is increasingly urgent, given their crucial role in economies facing global aging trends. Thus, our study specifically investigates the effects of digital stress on work engagement within the underrepresented demographic of aging employees.

Our study based on the JD-R model (Bakker & Demerouti, 2007), this study explores the stress and challenges faced by aging employees in a digitalized workplace, particularly those related to the complexity and rapid

changes of digital tools and AI technologies. Our perspective extends the JD-R model to the digital workplace, providing a new framework for understanding technological stress, including AI-related challenges, and employees' adaptability to these advancements. Second, the study specifically focuses on the digital stress that aging employees may experience when engaging with new technologies, addressing a key research gap concerning the adaptation challenges faced by aging workers in the digitalized workplace. We highlight the negative effects of unfamiliarity and the perception of obsolescence with digital tools, which can lead to work-related anxiety and reduced work engagement among aging employees. Third, our research demonstrates that algorithmic competency—a specialized personal resource that enables employees to decode the underlying logic and predictive behaviors of algorithmic systems (Zhou et al., 2025), can effectively reduce the stress and anxiety experienced by aging employees when using digital tools. We propose that aging employees' algorithmic competency not only aids their adaptation to the digital work environment but also alleviates the psychological burden associated with digital technologies, ultimately enhancing their work engagement. Finally, our study offers targeted management strategies for enterprises and organizations to support employees, particularly aging workers, during the digital transformation process. We aim to mitigate negative emotional responses to digital changes, while also enhancing work performance and fostering a greater sense of engagement.

Digital stress on work engagement

Given the widespread use of technology in both everyday life and the workplace, the impact of technology on individuals' perceived stress levels has attracted



increasing research attention, particularly among aging workers (e.g., [Matthes et al., 2020](#); [Nastjuk et al., 2024](#)). Digital stress is a psychological strain resulting from the demands imposed by digital tools and systems ([Tarafdar et al., 2019](#)). This form of stress can undermine work engagement, which is defined as a positive and fulfilling work-related state characterized by vigor, dedication, and absorption ([Schaufeli et al., 2002](#)).

According to the JD-R model, job requirements encompass factors that demand significant energy and effort from employees ([Bakker & Demerouti, 2007](#)). Prolonged, excessive job demands can lead to fatigue and burnout ([Demerouti et al., 2001](#); [Schaufeli & Bakker, 2004](#)). Digital stress, a contemporary job requirement ([Li et al., 2025b](#)), stems from the relentless stream of work-related communications, social media engagement, and the constant pressure to remain hyperconnected. These digital stressors consume employees' mental resources, reducing their engagement at work ([Funke et al., 2026](#); [Low et al., 2025](#); [Li et al., 2025b](#)). Over time, sustained digital stress can lead to burnout, eroding employees' positive emotions and effort in their work. Moreover, the widespread adoption of digital technology has enabled employees to be contacted and required to respond almost anytime and anywhere ([Matthes et al., 2020](#); [Nastjuk et al., 2024](#)). This continuous digital presence is called digital constancy, which often makes employees feel unable to escape work pressure, thereby increasing their psychological burden ([Tarafdar et al., 2015](#)). For those employees who need to maintain a high frequency of interaction at work, being unable to completely disconnect from digital devices can easily lead to stress and weaken their work motivation and commitment. Based on the JD-R model, we believe that when job requirements exceed an employee's coping capacity ([Bakker & Demerouti, 2007](#)), the employee's energy will gradually be depleted, leading to a decline in work engagement. Digital stress, especially information overload and continuous digital interaction, will occupy the cognitive and emotional resources of employees, making it difficult for them to concentrate on performing efficient work ([Funke et al., 2026](#); [Low et al., 2025](#)). When employees encounter continuous digital stress at work and do not have sufficient resources to alleviate it, their work enthusiasm and engagement are usually negatively affected, manifested as lower work engagement ([Schaufeli et al., 2009](#)).

Mediating effect of workplace anxiety

Digital stress can trigger negative emotional responses ([Funke et al., 2026](#); [Low et al., 2025](#)), particularly situational workplace anxiety—a transient state of apprehension directly elicited by specific environmental stressors ([McCarthy et al., 2016](#)). Unlike dispositional anxiety, which reflects a stable personality trait, situational anxiety arises from contextual pressures such as the overwhelming demands of constant connectivity and the inability to disengage from work tasks ([McFarland & Hay, 2023](#)). Employees facing high levels of digital stress are thus more likely to experience this form of anxiety, as they struggle to meet escalating work demands, deadlines, or performance expectations ([Marsh et al., 2024](#)). When

such situational anxiety is activated, employees' mental resources are diverted toward coping with the stressor, leaving limited cognitive and emotional capacity for proactive and sustained engagement in their work ([Pingel et al., 2019](#); [Shin & Hur, 2021](#)).

Work engagement is characterized by vigor, dedication, and absorption ([Schaufeli et al., 2006](#); [2009](#)), whereas situational anxiety manifests as distraction, worry, and emotional exhaustion ([Bertrams et al., 2013](#); [Strack et al., 2015](#))—states that are antithetical to the focused immersion required for deep engagement ([McCarthy et al., 2016](#)). When digital stress elevates anxiety levels, employees' cognitive resources are diverted toward threat monitoring and emotion regulation ([Pingel et al., 2019](#); [Shin & Hur, 2021](#)), thereby depleting the mental energy available for proactive and positive work engagement. As a result, anxious employees are less likely to feel energized or dedicated, ultimately undermining their overall work engagement ([Li et al., 2025b](#)). Thus, workplace anxiety functions as a mediating mechanism, explaining the negative impact of digital stress on work engagement.

Within the framework of the Job Demands-Resources (JD-R) model ([Bakker & Demerouti, 2007](#)), digital stress can be viewed as a job demand that depletes employees' resources and increases their emotional burden ([Marsh et al., 2024](#)), leading to heightened situational workplace anxiety ([McFarland & Hay, 2023](#)). This state of anxiety, in turn, further depletes employees' psychological resources, impairing their ability to engage fully in their work ([Cheng & McCarthy, 2018](#); [Rinsky-Halivni et al., 2022](#)). Therefore, workplace anxiety plays a critical mediating role in the relationship between digital stress and work engagement, illustrating how a specific situational stressor reduces positive work-related states through the depletion of immediate psychological resources ([Crawford et al., 2010](#); [Saleem et al., 2022](#)). Therefore, we propose that workplace anxiety plays a mediating role in the relationship between digital stress and work engagement.

Moderating effect of algorithmic competency

According to the JD-R model, an employee's ability to meet job demands depends on the resources they have at their disposal ([Bakker & Demerouti, 2007](#); [Bakker & Demerouti, 2017](#); [Demerouti & Bakker, 2011](#)). Algorithmic competency can be regarded as a crucial personal resource that enables employees to decode the underlying logic and predictive behaviors of algorithmic systems ([Zhou et al., 2025](#)) and can effectively reduce the stress and anxiety experienced by aging employees when using digital tools. In the context of digital stress (which stems from algorithmic systems, data flow, and automated decision-making), employees with high algorithmic capabilities can better understand the logic of the system, predict its behavior, and maintain a sense of control ([Benlian et al., 2022](#); [Kellogg et al., 2020](#); [Parker & Grote, 2022](#)). This control helps reduce the uncertainty and helplessness often associated with digital stress, thereby weakening the psychological pathways that lead to anxiety ([Cram et al., 2022](#); [Wu et al., 2023](#)). In contrast, employees with lower algorithmic competency may feel overwhelmed by the complexity of the technology, heightening their sense of

uncertainty and increasing their anxiety (Parker & Grote, 2022; Zhou et al., 2025).

Moreover, according to the stress cognitive appraisal and coping, an individual's assessment of the stressor (primary assessment) and their assessment of their own coping ability (secondary assessment) jointly determine the stress response (Dewe, 1991; Folkman et al., 1986). Employees with high algorithmic competency are more inclined to believe that they can manage digital demands through effective operation, adjustment of settings, or interpretation of outputs (high secondary assessment) (Parker & Grote, 2022). This prompts them to adopt problem-focused adaptive coping strategies rather than emotion-focused ineffective avoidance or struggle. This proactive coping behavior can more directly address the stressor itself, thereby resolving the digital stress before it leads to severe and persistent anxiety (Ofem, 2025). Therefore, algorithmic competency alters the coping behavior patterns of employees and regulates the relationship between stress and anxiety.

Goals of the Study

Our study is to systematically investigate the influence of digital stress on the work engagement of aging employees within the framework of the Job Demands-Resources (JD-R) model. By conceptualizing digital stress as a contemporary job demand and algorithmic competency as a vital personal resource, this study seeks to elucidate the psychological mechanisms through which technological strain undermines employee vigor and dedication. Specifically, our research aims to examine the direct impact of digital stress on work engagement and explore the potential mediating role of workplace anxiety in this relationship. Furthermore, we identify a critical boundary condition by testing whether algorithmic competency serves as a buffering resource that mitigates the negative emotional responses and subsequent disengagement among aging workers. Ultimately, this study validates an integrated moderated mediation model to provide a comprehensive understanding of how older employees adapt to digital transformation, thereby offering practical insights for sustainable human resource management. Figure 1 shows our theoretical model. Based on these research objectives, we propose the following hypotheses:

Hypothesis 1: Digital stress is negatively related to work engagement.

Hypothesis 2: Workplace anxiety mediates the relationship between digital stress and work engagement.

Hypothesis 3: Algorithmic competency moderates the positive relationship between digital stress and workplace anxiety. Specifically, the positive relationship is weaker for employees with higher levels of algorithmic competency.

Hypothesis 4: Algorithmic competency moderates the indirect effect of digital stress on work engagement through workplace anxiety. Specifically, this indirect effect is weaker for employees with higher levels of algorithmic competency.

Method

Participants and setting

Our study collected data from 305 aging employees across multiple industries in major cities in eastern China. To mitigate potential common method bias and track the temporal development of the proposed mechanisms, we implemented a strict participant matching process. At Time 1, 400 questionnaires measuring digital stress and demographic variables were distributed, yielding 382 responses. Two weeks later (Time 2), we invited the T1 respondents to report their workplace anxiety and algorithmic competency, resulting in 345 completed surveys. At Time 3 (another two weeks later), we collected work engagement data from the T2 respondents, obtaining 318 responses. After rigorous data cleaning and matching via unique participant codes, the final dataset comprised 305 valid responses, representing a questionnaire validity rate of 76.25%. Table 1 details the sample distribution by industry and primary job categories, providing a clear picture of the occupational contexts under investigation.

We obtained a final dataset of 305 valid responses, resulting in a questionnaire validity rate of 76.25%. Among these participants, 50.8% were male, with an average age of 50.78 years ($SD = 4.68$) and an average tenure of 22.86 years ($SD = 7.48$). Additionally, 83.9% held a college degree or higher, and the average weekly working hours were 42.54 h ($SD = 8.23$).

Measures

All responses were collected using five-point Likert-type options, ranging from 1 (strongly disagree) to 5 (strongly agree). Because the data were collected from Chinese companies, we used scales that had been previously validated in the Chinese context. For scales originally written in

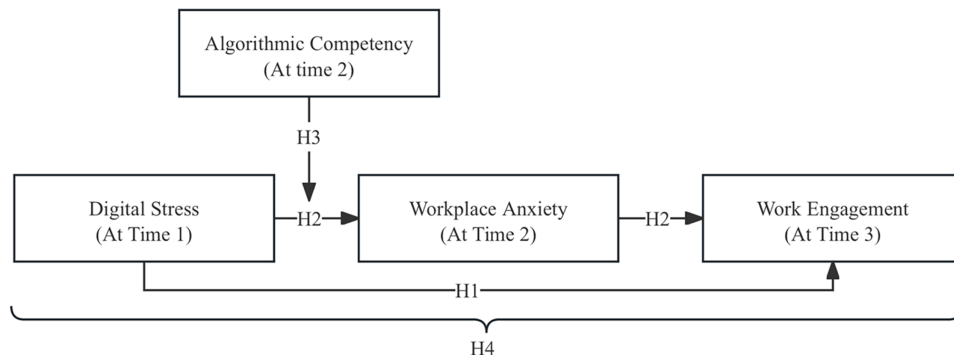


Figure 1. Theoretical model of study. Note. H = Hypothesis. H4 is an integrative model of moderated mediation.

Table 1. Sample characteristics by industry and job category (N = 305)

Industry	Sample size	Primary job categories	Percentage (%)
Banking	45	Front-office (teller, loan officer), Back-office (financial analyst, compliance officer)	14.8%
Retail	52	Customer-facing (sales associate, store supervisor), Logistics (inventory manager)	17.0%
Education	123	Teaching staff (lecturer, vocational trainer), Administrative (academic advisor)	40.3%
Manufacturing	36	Production (line supervisor, quality inspector), Support (maintenance technician)	11.8%
Technology	49	Technical (IT support, data analyst), Non-technical (project coordinator)	16.1%

Note. N = sample size; IT = Information Technology. Percentages represent the proportion of the total sample from each industry.

English, we rigorously followed Brislin's (1986) procedures for translating the survey items.

Digital Stress. At Time 1, employee self-evaluated digital stress using the 10-item scale developed by Funke et al. (2026). A sample item is "I spend too much time responding to notifications or messages". The Cronbach's alpha for this scale was 0.84.

Workplace Anxiety. At Time 2, employee self-evaluated workplace anxiety using the 8-item scale developed by Mccarthy et al. (2016). A sample item is "I worry that I will not be able to successfully manage the demands of my job". The Cronbach's alpha for this scale was 0.91.

Algorithmic Competency. At Time 2, employee self-evaluated algorithmic competency using the 12-item scale developed by Zhou et al. (2025). A sample item is "I can utilize the platform's APP functions (such as reporting anomalies or making appeals) to address the loopholes in the algorithm management." The Cronbach's alpha for this scale was 0.91.

Work Engagement. At Time 3, employee self-evaluated short-term work engagement using the 9-item scale developed by Schaufeli et al. (2006). A sample item is "I am immersed in my work". The Cronbach's alpha for this scale was 0.90.

Control Variables. We controlled for employees' weekly working hours because it is related to work engagement (e.g., Bakker & Sanz-Vergel, 2013). Additionally, we controlled for age, gender, tenure, and education level in this study because prior research has demonstrated that these variables impact work engagement (Kim & Kang, 2017; Schaufeli et al., 2006).

Procedure

This study received ethical approval from Jinhua Open University's Research Ethics Committee (approval ID: JOU2025-07-011). Prior to participation, all respondents reviewed the study introduction and provided informed consent. Participating organizations authorized the research, and we established a confidential coding system that assigned anonymous identifiers to each employee. Survey distribution utilized WeChat, China's dominant mobile messaging platform.

Data analysis

We performed all statistical procedures using SPSS 27.0. Initial analyses included descriptive statistics and correlation matrices for all variables. Common method bias was evaluated using Harman's single-factor technique. We tested the moderated mediation hypotheses using Hayes' (2018) PROCESS macro Model 7, specifying Digital Stress as the predictor, Work Engagement as the outcome, Workplace Anxiety as the mediating mechanism, and Algorithmic Competency as the boundary condition. Indirect effects were estimated through bias-corrected bootstrapping (5000 iterations), generating 95% confidence intervals. Effects were deemed statistically reliable when confidence intervals excluded zero.

Common method deviation test

Following Podsakoff et al.'s (2003) recommendations, we incorporated procedural remedies during study design, including temporal separation of measurements. Post-hoc assessment via Harman's single-factor test revealed that the largest factor accounted for 25.83% of total variance—well below Podsakoff et al.'s 40% criterion, suggesting negligible common method variance. Additionally, the fit indices for the single-factor model's confirmatory factor analysis, shown in Table 2, did not meet acceptable standards ($\chi^2 = 4306.43$, $df = 702$, $RMSEA = 0.13$, $SRMR = 0.15$, $CFI = 0.41$, $TLI = 0.38$), further confirming the lack of significant common method bias among the study variables. These findings provide strong evidence for the validity of the study.

Measurement model

We performed a confirmatory factor analysis (CFA) using Mplus software to evaluate the convergent and discriminant validity of a measurement model consisting of four latent factors. The CFA results, shown in Table 2, indicate that the proposed four-factor model exhibits excellent goodness-of-fit indices ($\chi^2/df = 2.63$, $CFI = 0.91$, $TLI = 0.90$, $RMSEA = 0.05$, $SRMR = 0.05$), with all factor loadings surpassing 0.70. Furthermore, the measurement model demonstrated acceptable reliability and validity. The Cronbach's alpha and Composite Reliability (CR) for all variables were above 0.70. Specifically, the Average Variance Extracted (AVE) for digital stress, workplace

Table 2. Results of confirmatory factor analysis (N = 305)

Models	χ^2	df	χ^2/df	RMSEA	SRMR	CFI	TLI
Four factor models (hypothesis)	1836.11	696	2.64	0.05	0.05	0.91	0.90
Three factor models (B + C)	3140.55	698	4.50	0.10	0.13	0.66	0.61
Two factor models (B + C + D)	3853.64	701	5.49	0.12	0.15	0.49	0.46
One factor models (A + B + C + D)	4306.43	702	6.13	0.13	0.15	0.41	0.38

Note. A = Digital stress; B = Workplace anxiety; C = Algorithmic competency; D = Work engagement; “+” indicates fusion. χ^2 = chi-square; df = degrees of freedom; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; CFI = Comparative Fit Index; TLI = Tucker–Lewis Index; N = sample size.

Table 3. Descriptive statistics and correlation for variables

Variables	M	SD	1	2	3	4	5	6	7	8	9
1. Gender	0.41	0.49									
2. Age	50.78	4.68	−0.07								
3. Education	15.08	1.88	−0.15**	−0.17**							
4. Work hours weekly	42.54	5.80	−0.06	−0.11	−0.16**						
5. Tenure	22.86	7.48	−0.10	0.54***	0.11	−0.04					
6. Digital stress	2.76	0.73	0.04	−0.11*	0.06	−0.02	0.02	(0.84)			
7. Workplace anxiety	2.50	0.87	0.02	−0.10	−0.01	0.05	−0.05	0.56***	(0.91)		
8. Algorithmic competency	3.47	0.78	−0.06	0.01	−0.04	0.06	−0.07	−0.05	−0.18**	(0.91)	
9. Work engagement	3.65	0.74	−0.07	0.08	−0.02	0.02	0.02	−0.35***	−0.38***	0.42***	(0.90)

Note. M = Mean; SD = Standard Deviation. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ (The same below).

anxiety, algorithmic competency, and work engagement were 0.52, 0.58, 0.55, and 0.51, respectively, all exceeding the 0.50 criterion for convergent validity. These results confirm the distinctiveness of the study variables, validating the proposed model and establishing a strong foundation for further analyses.

Descriptive statistics and correlations

Table 3 presents the descriptive statistics for each variable, including means, standard deviations, and correlations. The results reveal significant negative correlations between digital stress and work engagement ($r = -0.35, p < 0.001$) and between workplace anxiety and work engagement ($r = -0.38, p < 0.001$). These findings provide preliminary evidence supporting the negative predictive relationship between digital stress and employee work engagement.

Hypothesis testing

Table 4 shows that the relationship between digital stress and work engagement is significant ($\beta = -0.34, p < 0.001$). Thus, Hypothesis 1 was supported.

Table 4 indicates significant relationships between digital stress and workplace anxiety ($\beta = 0.56, p < 0.001$), workplace anxiety and work engagement ($\beta = -0.28, p < 0.001$), and digital stress and work engagement ($\beta = -0.18, p < 0.01$). We tested the indirect effect using Model 4 in PROCESS and found that digital stress significantly affects work engagement through workplace

anxiety (effect = $-0.16, SE = 0.05, 95\% CI [-0.26, -0.07]$). Thus, Hypothesis 2 was supported.

Table 4 reveals a significant relationship between the interaction term of digital stress and algorithmic competency and workplace anxiety ($\beta = -0.13, p < 0.05$). In accordance with standard practices for interpreting interaction effects, both digital stress and algorithmic competency were mean-centered before forming their product term. This procedure reduces multicollinearity between the interaction term and its components and produces more interpretable simple slopes (Aiken et al., 1991). We examined the moderating effect using Model 1 in PROCESS (Hayes, 2017) and found that algorithmic competency significantly moderates the relationship between digital stress and workplace anxiety (effect = $-0.19, SE = 0.07, 95\% CI [-0.33, -0.04]$). To further explore this interaction, we probed the effect at one standard deviation above and below the mean of algorithmic competency (Aiken et al., 1991). The simple slopes test (see Figure 2) demonstrated that the effect of digital stress on workplace anxiety was weaker at higher levels of algorithmic competency (+1 SD; $\beta = 0.71, t = 11.83, p < 0.001$) compared to lower levels (−1 SD; $\beta = 0.52, t = 6.60, p < 0.001$). Thus, Hypothesis 3 was supported.

We assessed the indirect mediation effect of workplace anxiety at different levels of algorithmic competency using Model 7 in PROCESS (Hayes, 2017). The results showed that the indirect effect of digital stress on work engagement through workplace anxiety was significant at both low and high levels of algorithmic competency. Specifically, at low

Table 4. Regression analysis model

Variables	Workplace anxiety			Work engagement		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variable						
Gender	0.02	−0.01	−0.02	−0.07	−0.05	−0.06
Age	−0.11	−0.01	−0.01	0.09	0.03	0.03
Education	−0.01	−0.02	−0.02	−0.02	−0.07	−0.01
Work hours weekly	0.06	0.06	0.07	−0.01	−0.01	0.01
Tenure	0.02	−0.04	−0.08	−0.04	0.00	−0.01
Independent variable						
Digital stress		0.56***	0.59***		−0.34***	−0.18**
Mediating variable						
Workplace anxiety						−0.28***
Moderating variable						
Algorithmic competency			−0.19***			
Interaction terms						
Digital stress * Algorithmic competency			−0.13*			
R^2	0.01	0.32	0.36	0.01	0.12	0.18
ΔR^2		0.30***	0.34***		0.11***	0.17***

Note. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

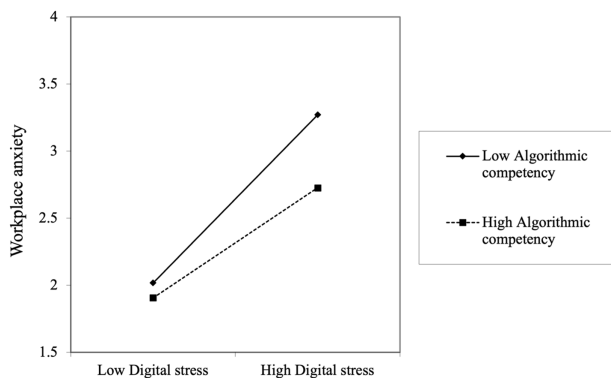


Figure 2. Moderating effect of algorithmic competency on the relationship of digital stress and workplace anxiety. Note. SD = Standard Deviation. Low = −1 SD; High = +1 SD of algorithmic competency.

levels of algorithmic competency, the effect was -0.20 ($SE = 0.06$, 95% CI $[-0.32, -0.10]$), and at high levels, the effect was -0.13 ($SE = 0.05$, 95% CI $[-0.25, -0.06]$). Therefore, Hypothesis 4 was supported.

Discussion

Our study offers several important theoretical contributions to the understanding of digital stress, work engagement, and the dynamics of aging employees in the modern workplace. First, the study extends the Job Demands–Resources model by focusing on aging employees who experience digital stress in the era of digitalization and artificial intelligence (Bakker & Demerouti, 2007; Bakker & Demerouti, 2017). Specifically, digital stress is conceptualized as a job demand, whereas algorithmic competency is positioned as a job resource (Parker & Grote, 2022). Grounded in the JD-R model, which emphasizes the interplay between job demands and resources,

this study elucidates the distinct mechanisms through which digital stress influences older employees. Moreover, it demonstrates how algorithmic competency serves as a buffering resource, mitigating the adverse effects of digital stress on work engagement. By integrating these constructs, our research extends the JD-R framework, enhancing its applicability in contexts characterized by rapid technological change and digital transformation (e.g., Van Steenbergen et al., 2018).

Second, this study reveals the mediating role of workplace anxiety in the relationship between digital stress and work engagement. While prior research has predominantly focused on the direct effects of digital stress on employee outcomes (e.g., Czaja et al., 2018; Funke et al., 2026), the psychological pathway through which such stress influences engagement—particularly via anxiety—remains underexplored. Our findings underscore the emotional toll imposed by digital demands on aging workers, thereby providing a more nuanced understanding of the mechanism through which digital stress diminishes work engagement.

Third, this study underscores the moderating role of algorithmic competency, contributing to the evolving literature on digital workplace resources (e.g., Parker & Grote, 2022; Zhou et al., 2025). Our findings position algorithmic competency as a specialized personal resource that extends beyond general digital literacy to specifically address the unique stressors faced by aging employees in automated environments (Zhou et al., 2025). We demonstrate that the capacity to decode the underlying logic and predict the behaviors of algorithmic systems does more than enhance performance; it serves as a critical psychological protective factor that mitigates workplace anxiety by restoring a sense of agency and control. By developing algorithmic competency, employees—particularly aging workers who face greater adaptation challenges—become better equipped to

manage digital stress (Zayid et al., 2024), thereby mitigating its negative impact on engagement. This highlights the importance of fostering algorithmic competency as a targeted intervention for building workforce resilience in increasingly technology-driven environments (Setiawan et al., 2025; Zhou et al., 2025).

Finally, the study advances our understanding of the aging workforce's interaction with digital technologies. By focusing on aging employees, it fills a gap in the literature that often overlooks this demographic in the context of digital transformation. The findings suggest that aging workers may face unique challenges in adapting to digital technologies, with implications for both theoretical models of digital stress and practical interventions aimed at enhancing work engagement in this group.

Implications for research and practice

Our study has several practical contributions. First, organizations should recognize the unique challenges that aging employees face in adapting to digital technologies. Given that digital stress can significantly affect work engagement, companies should provide targeted support to older workers, ensuring that they have the resources and training necessary to effectively cope with digital demands (Parker & Grote, 2022; Zhang & Chen, 2024). This might involve offering tailored digital literacy programs (Lee & Kim, 2019), mentorship opportunities (Fan et al., 2025), or specialized support for technology adoption to reduce stress and enhance engagement among aging employees.

Second, our study emphasizes the importance of fostering algorithmic competency in the workforce, particularly for older employees who may struggle with rapidly advancing technologies (Parker & Grote, 2022). Organizations can implement training initiatives that focus on improving algorithmic skills and overall digital literacy (e.g., Spurava & Kotilainen, 2023). By doing so, organizations not only help employees better manage digital stress but also improve their overall productivity and engagement. Encouraging a continuous learning culture and offering opportunities for skill development will allow employees to feel more confident and competent in using digital tools (Trenerry et al., 2021), thus reducing the anxiety often associated with digital transformation.

Third, employers should be mindful of the emotional burden that digital stress can place on aging workers. Given that workplace anxiety mediates the relationship between digital stress and work engagement, it is crucial for organizations to implement mental health support systems and create an environment that minimizes unnecessary digital pressures (Naslund et al., 2020). This might include providing access to counseling, stress management workshops, or stress-reducing technologies (e.g., Berger et al., 2024), ensuring that employees feel supported in managing their emotional well-being amidst digital transitions.

Finally, organizations should consider redesigning job roles and workflows to better accommodate older employees' needs in the digital age (Funke et al., 2026; Low et al., 2025). This could involve adjusting tasks to reduce unnecessary complexity or ensuring that digital tools and platforms are user-friendly and intuitive, reducing the

potential for confusion and frustration (Wrede et al., 2023). By creating a more inclusive and supportive digital work environment, companies can improve the well-being and performance of aging employees, while also boosting their overall work engagement. Moreover, the findings highlight the need for organizations to take a proactive approach to digital transformation. In addition to focusing on technology deployment, companies should also be aware of the human side of digital change (Elliott et al., 2021; Wilson & Daugherty, 2018). By investing in programs that address both the technical and emotional aspects of digital transitions (e.g., Funke et al., 2026; Low et al., 2025; Zhou et al., 2025), organizations can help their employees—especially older workers—adapt more successfully and thrive in an increasingly digital and AI-driven workplace.

Limitations and future research directions

Despite its theoretical and practical implications, our study has several limitations that should be addressed in future research. First, we relied on self-reported measures, which can be susceptible to common method bias (Cooper et al., 2020; Podsakoff et al., 2024). Future research could incorporate multi-source data, including supervisor assessments and objective measures of digital stress, to enhance the robustness of the findings. Furthermore, although our multi-company sampling strategy bolsters the generalizability of the findings, it prevents us from disentangling the confounding effects of organizational-level factors. A promising direction would be to employ a single-organization longitudinal design, which would allow researchers to control for organizational context and better model the temporal evolution of the proposed relationships.

Second, our time-lagged design employed in this study constrains our ability to draw robust causal inferences regarding the relationships among digital stress, algorithmic competency, workplace anxiety, and work engagement. Future research should adopt longitudinal designs with extended time intervals or experimental approaches to better clarify the temporal dynamics and validate causal pathways among these constructs, thereby strengthening the evidence base. While the scale has demonstrated reliability in measuring digital stress, its application to older adults in a workplace setting remains an area of concern. Although the scale covers relevant dimensions of digital stress, such as social anxiety, constant availability, and overwhelming digital engagement, it was not specifically designed or validated for aging workers. This may limit the generalizability of our findings; this should consider developing or validating digital stress scales that are specifically tailored to aging workers in workplace environments to ensure more accurate and relevant measurements.

Third, the generalizability of our findings may be limited by the study's focus on aging employees in China. Specific cultural dimensions prevalent in the Chinese context, such as high collectivism (Earley, 1989; Ma et al., 2014) and power distance (Farh et al., 2007), could shape the observed relationships. For instance, collectivism might amplify the stress on aging employees to conform to digital demands due to group expectations

(Probst & Lawler, 2006), while high power distance could make them more susceptible to top-down technological implementation, thereby intensifying digital stress. Future research should explore these dynamics across diverse cultural and national contexts, incorporating cross-cultural comparisons or broader demographic samples to assess the applicability of the findings in globalized work environments. Moreover, although our multi-company and multi-sector sampling strategy bolsters the external validity of the findings, it may overlook specific industry-level factors. Future research could utilize a single-organization design or conduct sector-specific comparisons to further refine our understanding of digital stress among aging workers.

Finally, although algorithmic competency was examined as a moderator, other individual or organizational factors, such as job autonomy or organizational support (Caesens & Stinglhamber, 2014; De Spiegelaere et al., 2014), were not explored. These factors may play a significant role in buffering the effects of digital stress on work engagement. Future research could investigate additional moderators or mediators, such as organizational support (Caesens & Stinglhamber, 2014), or psychological resilience (Meng et al., 2023), to provide a more comprehensive understanding of the mechanisms driving digital stress and its workplace implications.

Conclusion

Our study demonstrates that workplace anxiety plays a crucial role as a mediator in the relationship between digital stress and work engagement, suggesting that the emotional and cognitive burdens of digital job demands can significantly shape how employees engage with their work. Moreover, the moderating effect of algorithmic competency emphasizes the importance of equipping aging employees with the necessary skills to effectively navigate technological tools.

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