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Pilot Study on the Validity and Reliability of a Multi-Dimensional Stress Management Instrument in Medium-Sized Manufacturing Firms in China

Rui Guo[1], Beni Widarman Yus Kelana[1], Almetere Eman Safar[2], Almi Mahmod[1], Zhenpeng Ji[3], Lei Cheng[3]

[1]Azman Hashim International Business School, Universiti Teknologi Malaysia Johor Bahru, Malaysia, [2]A-1-1, Taif University, At taif, 26576, Makkah Province, Saudi Arabia, [3]Shandong Qinlu Energy Technology Co., Ltd, Jinan, China

Corresponding Author Email: guorui@graduate.utm.my

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Abstract

The digital transformation of China's manufacturing industry has exacerbated employee stress, particularly in medium-sized enterprises. Existing stress measurement tools often focus on isolated stress factors, neglecting the complex interplay of personal, work-related, and technological influences. This study develops and validates a multidimensional instrument that integrates cognitive stress appraisal, emotional regulation, behavioral coping strategies, workload perception, AI-enabled ease of use (AI-EoU), and stress management. Survey data from 50 employees in medium-sized manufacturing firms were analyzed using Exploratory Factor Analysis(EFA), Cronbach's α, and Pearson correlations. The results demonstrate strong construct validity (KMO > 0.8) and high reliability (Cronbach's α> 0.88). This research extended the Transactional Model of Stress and Coping(TMSC) by positioning AI-EoU as a secondary appraisal resource highlighting its role in influencing stress adaptation in digitalized workplaces. The developed instrument offers firms a robust tool for evaluating and enhancing stress management predictors in technology-driven environments.

Keywords: Stress Management, AI-EoU, Coping, Manufacturing, TMSC

Introduction

The rapid digital transformation of China's manufacturing industry has intensified work stress, especially in medium-sized enterprises in Shandong Province, a major industrial hub(Xu et al., 2020). Employees face multiple stressors, including production targets, technological adaptation, and heavy workload, which significantly affect efficiency and well - being (Hu & Fan, 2024; China Labour Watch, 2023). Existing stress management approaches, however, often rely on unidimensional tools that capture only isolated aspects such as emotional regulation or behavioral coping, limiting a comprehensive understanding of stress dynamics in complex work environments (Murphy, 1996).

Current instruments rarely integrate cognitive, emotional, behavioral, and work-related predictors, nor do they account for technological factors such as employees' interaction with AI systems. This gap is particularly salient in manufacturing contexts where digital technologies are increasingly embedded in daily operations (Acarturk & Mucen., 2022; Tortorella et al., 2025). Addressing this limitation, the present study develops and validates a multidimensional stress management measurement tool, incorporating cognitive stress appraisal, emotional regulation, behavioral coping strategies, workload perception, AI - enabled ease of use (AI - EoU), and stress management. All scales were adapted or adopted from existing literature to ensure the validity and reliability of the instrument

This study makes two contributions. Theoretically, it extends stress and coping frameworks by positioning AI - EoU as a mediating factor, highlighting how technology usability can shape employees' coping capacity (Davis, 1989). Practically, it provides manufacturing enterprises with a reliable instrument to assess stress management and design more effective interventions (Mohamed et al., 2022). By focusing on medium-sized firms in China, the study also delivers industry and region, specific insights into managing employee well - being in high pressure, technology intensive environments (Shandong Bureau of Statistics, 2022).

In line with Lazarus and Folkman's (1984) TMSC, this study positions AI-enabled ease of use (AI-EoU) as a situational resource in secondary appraisal, where usability perceptions shape employees' evaluation of coping resources. Prior research on technostress shows that intuitive systems lower cognitive load and enhance perceived control (Tarafdar et al., 2015). By embedding AI-EoU into the stress–coping framework, we extend classical theory to capture the realities of technology-intensive workplaces. Table 1.1 summarizes the constructs, their theoretical sources, and representative indicators.

Table 1.1
Variables used in this research

No.	Pilot Test Constructs	Scale Source	Sample Items Adopted	Sample Items Adapted
1	Cognitive Stress Appraisal	Fliege et al., 2005	★You have too many things to do.	
2	Emotional Regulation	Gouveia et al., 2018	★I keep my emotions to myself.	
3	Behavioral Coping Strategies	Zuckerman & Gagne., 2003	★I take direct action to get around the problem	
4	Workload Perception	Ross, J., 2017		★ I'm able to provide adequate support to **tasks** assigned to me.
5	AI-enabled Ease of Use	Kengue & Michel., 2020		★ I would find it easy to get AI to do what I want it to do.
6	Stress Management	Sonnentag & Fritz., 2007	★I feel like I can decide for myself what to do.	

The central problem this study addresses was how employees in digitally transforming manufacturing settings perceive and mobilize technological resources when evaluating and coping with workplace stress. This issue extends beyond psychometric validation: it speaks to contemporary debates in the social sciences concerning whether digital technologies primarily act as tools of empowerment or as mechanisms of intensified control(Haggart., 2019). In Chinese manufacturing, where the adoption of automation and AI is accelerating, perceptions of technology usability are critical(Xu et al., 2020). Empirical evidence has shown that perceived ease of use (PEOU) significantly shapes technology adoption in this sector (Cao et al., 2020). Building on this insight, we conceptualize AI-Enabled Ease of Use (AI-EoU) not only as a determinant of adoption but also as a secondary appraisal resource that may alleviate technostress and enhance stress management(Tarafdar et al., 2019). In doing so, this study aimed to connect the micro-level experience of employees with broader debates on technological management, worker agency, and well-being(Lee, 2018).

Prior work in Chinese manufacturing underscores the relevance of ease-of-use perceptions in shaping organizational and individual outcomes. In a large-scale survey of manufacturing firms, Cao et al. (2020) confirmed that PEOU mediated the relationship between perceived norms and the adoption of automation technologies, demonstrating the validity of usability constructs in this context. Furthermore, Qu & Kim. (2025) showed that PEOU within a TAM-TOE framework significantly influenced AI adoption and innovation outcomes among apparel manufacturing MSMEs in China. These findings suggest that AI-EoU operates as a pivotal perception in shaping how manufacturing organizations and their employees respond to technological change. At a broader level, Yang et al. (2022) reported that industrial AI transformation across Chinese cities was positively associated with workers' mental health, indicating that technological diffusion may contribute to reduced stress. Taken together, these studies establish a strong contextual foundation for our argument that AI-EoU functions as a resource within the transactional process of coping, with direct implications for technostress dimensions such as techno-overload and techno-complexity.

Methodology

This pilot study utilized SPSS 30.0 for data analysis, employing Exploratory Factor Analysis (EFA), Cronbach's α coefficient, and Pearson correlation analysis to assess the reliability and validity of the measurement instrument. In conducting EFA, an unrotated solution was adopted to directly present the original factor extraction results. This choice reflects the study's primary aim of evaluating the overall construct validity and discriminant capacity of the instrument rather than maximizing factor interpretability. To verify the suitability of the data for factor analysis, the Kaiser-Meyer-Olkin (KMO) statistic (> 0.7)and Bartlett's test of sphericity ($p < 0.001$) were performed, confirming the appropriateness of conducting EFA(Shrestha., 2021). Internal consistency was evaluated using Cronbach's α, with a recommended value greater than 0.7 indicating acceptable reliability(Tavakol & Dennick., 2011). Additionally, Pearson correlation analysis was applied to examine the positive associations between each independent variable and the core outcome variable(Hainmueller et al., 2016), such as stress management efficacy, thereby validating the predictive validity of the measurement tool.

The study sample consisted of 50 employees from medium-sized manufacturing enterprises in Shandong China. Although the sample size is limited, it was selected to reflect key characteristics of the target population, ensuring its relevance to the study context. All participants were experienced employees who voluntarily consented to participate. Additionally, strict ethical protocols were adhered to throughout the research process to ensure the protection of participants' privacy and data security. This study received ethical approval from the Ethics Committee of the University of Technology Malaysia (Approval No.: UTMREC-2025-166).

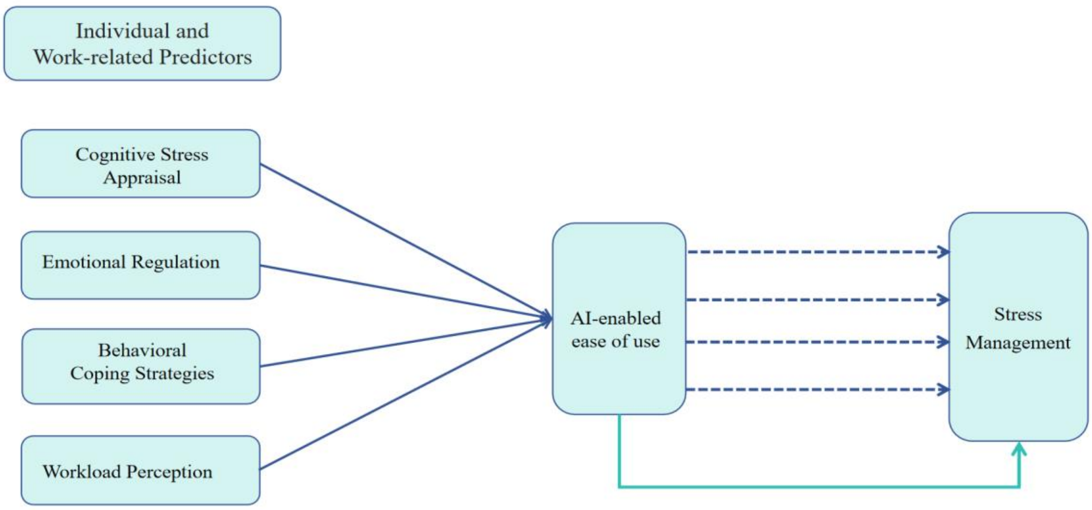

Figure 2.1 Prior Conceptual Model

As illustrated in Figure 2.1 adapted from Guo et al., 2025, the pilot framework integrates cognitive stress appraisal, emotional regulation, behavioral coping strategies, and workload perception as predictors of stress management efficacy, with AI-enabled ease of use serving as a mediating factor. This conceptual structure guides the empirical testing and highlights how personal, work-related, and technological resources jointly shape stress adaptation in manufacturing contexts.

Result

Exploratory Factor Analysis

This study utilized Exploratory Factor Analysis (EFA) to examine the construct validity of the measurement instrument (Table 3.1). The table presents detailed results of the KMO (Kaiser–Meyer–Olkin) measure and Bartlett's test of sphericity for each research variable. Specifically, the KMO values were 0.907 for individual and work-related predictors (comprising 4 independent variables and 52 items), 0.898 for AI-enabled ease of use (6 items), and 0.938 for stress management (16 items), all of which significantly exceeded the commonly used threshold of 0.8. Correspondingly, the p-values of Bartlett's test of sphericity were all less than 0.001, reaching a statistically significant level. These findings indicate that the data possess a high degree of structural validity and are highly suitable for factor analysis.

Results from the pilot test further revealed that the KMO values for all variables exceeded 0.89 (with the highest being 0.938), providing additional evidence for the presence of a significant common factor structure among the variables. Moreover, the revised scale demonstrated notable improvement in construct extraction compared to previous studies (Pillai et al., 2020; Kashive et al., 2020), as evidenced by its KMO threshold performance (all>0.89), which substantially surpassed the criteria set in earlier literature. In conjunction with the significant results of Bartlett's test (Svensen et al., 2007), it can be concluded that the current measurement instrument is capable of effectively differentiating among theoretical constructs, thereby exhibiting sound discriminant validity. These attributes establish a robust foundation for subsequent analytical procedures.

Table 3.1
Exploratory Factor Analysis

Research Variables	Research Variable	
	KMO	Barletts's Test of Sphericity value p<0.001
Individual and work-related predictors (4 independent variables)	0.907 (52 items)	0.000
AI-enabled Ease of Use	0.898 (6 items)	0.000
Stress Management	0.938 (16 items)	0.000

Reliability Analysis

To evaluate the internal consistency of the measurement scale, Cronbach's α coefficients were computed for all constructs based on pilot test data (Table 3.2). The results demonstrated robust reliability across all dimensions, with Cronbach's α values exceeding 0.885 for all constructs (range: 0.885–0.977), well above the accepted threshold of 0.7 (Pouy et al., 2025).

Table 3.2
Results of Reliability Analysis

Research Variables	Reliability Value	
	items	Cronbach's Alpha (α) **p<0.01
Cognitive Stress Appraisal	20 items	0.965
Emotional Regulation	10 items	0.936
Behavioral Coping Strategies	16 items	0.959
Workload Perception	6 items	0.885
AI-enabled Ease of Use	6 items	0.901

Notably, Cognitive Stress Appraisal showed the highest internal consistency (α=0.965, 20 items), indicating exceptional reliability. Similarly, Emotional Regulation (α=0.936, 10 items) and Behavioral Coping Strategies (α=0.959, 16 items) both achieved α values above 0.93, reflecting stable and coherent measurement of their respective psychological processes. Even constructs with fewer items, Workload Perception (α=0.885, 6 items) and AI-enabled Ease of Use (α=0.901, 6 items), maintained strong reliability, confirming that the abbreviated scales retained measurement precision.

These findings collectively validate the excellent internal consistency of the pilot-scale, with all constructs meeting or exceeding stringent reliability criteria. The high α values underscore the scale’s ability to produce dependable measurements, supporting its suitability for further use in formal research.

Correlation Analysis

Pearson correlation analysis was conducted to examine the relationships between the research variables and stress management efficacy in the pilot test (Table 3.3). AI-enabled Ease of Use exhibited a strong correlation with stress management (r=0.909, p<0.01), suggesting that this result may reflect a ceiling effect or sample characteristics, which could influence the strength of the relationship.

Table 3.3
Correlation of research variables

Research Constructs	Correlation Coefficient with Stress Management **p<0.01
	Research Constructs
Cognitive Stress Appraisal	r = 0.392**
Emotional Regulation	r = 0.283**
Behavioral Coping Strategies	r = 0.266**
Workload Perception	r = 0.261**
Total 4 IV	r = 0.418**
AI-enabled Ease of Use	r = 0.909**

Among the other predictors, Cognitive Stress Appraisal showed the second-strongest association (r = 0.392**, $p < 0.01$), indicating its notable influence on stress management outcomes. Both Emotional Regulation (r = 0.283**, $p < 0.01$) and Behavioral Coping Strategies (r = 0.266**, $p < 0.01$) demonstrated moderate, but statistically significant, relationships with stress management. Workload Perception (r = 0.261**, $p < 0.01$) had a slightly weaker yet still meaningful correlation, highlighting its role in stress management. The combined predictive power of all four independent variables (Total 4 IV) was substantial (r = 0.418**, $p < 0.01$), reinforcing their collective explanatory value for stress management outcomes.

The exceptionally high correlation between AI-enabled Ease of Use and stress management outcomes suggests methodological factors, such as scale redundancy or sample homogeneity, may be influenced this relationship. Cognitive Stress Appraisal emerged as the strongest individual predictor, followed by Emotional Regulation and Behavioral Coping Strategies, indicating the dominance of cognitive and regulatory processes in stress management. Overall, the moderate-to-strong correlations observed for all constructs support their theoretical relevance, though the extreme AI-ease-of-use correlation suggests refinement is needed in future studies.

Discussion

The factor and reliability evidence from the pilot study supports the instrument's multidimensional structure and internal consistency. Correlations with stress - management outcomes were uniformly positive yet moderate, demonstrating predictive validity without indicating redundancy among constructs. Notably, the relatively high correlation between AI-EoU and stress management likely reflected a halo effect, where favorable perceptions of AI usability were generalized to broader work experiences. Item refinements and a more heterogeneous sample reduced potential bias and multicollinearity, yielding relationships that are more theoretically consistent and empirically stable. This contrast underscores the iterative value of scale development in advancing from preliminary evidence to robust measurement.

Grounded in the TMSC, the results align with the view that AI - EoU functions as a situational resource in secondary appraisal. Higher perceived usability likely lowers cognitive load and increases perceived control, thus supporting adaptive coping choices. While the pilot study establishes associations, causal and indirect effects remain hypothesized mechanisms that warrant future testing using longitudinal or SEM - based analyses.

For organizations, simultaneously targeting psychological resources (e.g., training in cognitive appraisal and coping strategies) and technological resources (e.g., improving AI usability via user - centered design and just - in - time guidance) is advisable. Reducing workload perception and enhancing AI - EoU are complementary strategies for stress adaptation in technology - intensive manufacturing environments.

However, the findings are limited by the single - region, medium-sized manufacturing sample and the reliance on unrotated EFA and cross-sectional correlations. Future research should incorporate rotation sensitivity checks, normality/multicollinearity diagnostics, and mediation tests (bootstrapped indirect effects) to better establish the mechanisms at play.

Conclusion

This study provides coherent evidence that a multidimensional instrument capturing personal, work-related, and technological factors can validly and reliably assess stress management in medium-sized manufacturing firms. By positioning AI-EoU within TMSC, the study links technology usability to stress adaptation, adding a technology-driven dimension to stress–coping theory. The findings suggest that organizations should combine workload redesign with AI usability improvements and coping-skills training to enhance employees' stress-management capacity in digitalized workplaces.

Generalizability is constrained by context and design. Subsequent studies should test the hypothesized mediating mechanism using SEM/bootstrapping and examine temporal dynamics with longitudinal data, alongside diagnostic checks for assumptions and rotation sensitivity.

The result in this research add new perspective to ongoing debates by showing that, within manufacturing contexts, AI-EoU is strongly and positively associated with stress management. This finding complements earlier research demonstrating that ease-of-use perceptions foster technology acceptance in organizational settings (Cao et al., 2020; Qu & Kim., 2025), and it resonates with macro-level evidence linking AI transformation to improved worker well-being (Yang et al., 2022). At the same time, it diverges from studies in service industries that highlight the exacerbation of technostress through algorithmic control. For instance, Panchetti et al., (2023) found that workers’ acceptance of collaborative robots was closely tied to perceived usability and trust, suggesting that when technologies are experienced as usable, they may restore a sense of control rather than intensify stress. The finding in this research support this interpretation: in manufacturing environments, where work is highly routinized and efficiency-driven, ease-of-use may act as a critical buffer against cognitive stress, thereby enhancing employees’ coping capacity. This perspective highlights the importance of contextualizing technostress and points toward future studies that examine whether AI-EoU exerts similar buffering effects in other industrial settings. By demonstrating the critical buffering role of AI-EoU, this study ultimately shifts the perspective from viewing technology solely as a stressor to a potential resource that can be harnessed for employee well-being in the Industry 4.0 era.

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