

THE INFLUENCE OF AI READINESS ON EMPLOYEE PERFORMANCE: THE ROLE OF ORGANIZATIONAL SUPPORT

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Received : 05 July 2026; Revised: 14 July 2026; Accepted: 20 Sept 2026; Published: 01 Oct 2026

Vol: 6, Issue 1 (2026)

Doi: 10.5281/zenodo.22907259

Abstract

Keyword:

AI readiness;
employee
performance;
perceived
organizational
support;
artificial
intelligence
adoption;
Malaysia;
organizational
support theory



Artificial intelligence (AI) is spreading quickly through Malaysian workplaces under national agendas such as the Malaysia Digital Economy Blueprint (MyDIGITAL) and the National AI Roadmap 2021–2025. Even so, the human side of AI adoption has received little empirical attention, especially the question of whether employees' readiness for AI turns into better performance. Drawing on Organizational Support Theory and the Job Demands–Resources model, this study examines the influence of employee AI readiness on employee performance and tests whether perceived organizational support (POS) moderates that relationship. A quantitative cross-sectional survey was administered to 384 employees in Malaysian public-sector, private-sector and government-linked organizations. Data were analysed with IBM SPSS Statistics (version 29) using descriptive statistics, Pearson correlation and hierarchical moderated multiple regression, with the moderation probed through simple-slope analysis. AI readiness significantly and positively predicted employee performance ($\beta = .327$, $p < .001$), and so did perceived organizational support ($\beta = .324$, $p < .001$). The AI Readiness $\times$ POS interaction was also significant ($\beta = .126$, $p = .005$, $\Delta R^2 = .015$). The positive effect of AI readiness on performance was stronger when organizational support was high. The final model explained 29.1% of the variance in employee performance. The findings suggest that individual readiness alone is not enough: organizations must actively provide training, resources and a supportive climate to translate employees' AI readiness into performance gains. Implications for HR policy, AI-transition management and future research in Malaysia are discussed.



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Introduction

Artificial intelligence has moved from a specialised technical domain into everyday organizational practice. Machine learning, natural-language processing and, more recently, generative AI tools are

now built into recruitment, customer service, financial analysis, teaching and public administration. Scholars describe this shift as a sociotechnical transformation in which the value of AI depends as much on the people who work with it as on the technology itself (Dwivedi et al., 2021; Makarius et al., 2020). Field and experimental evidence shows that AI can substantially raise worker productivity. Noy and Zhang (2023) found that access to generative AI shortened completion times and improved output quality in professional writing tasks. Brynjolfsson et al. (2025) reported productivity gains among customer-support agents, with the largest benefits for less-experienced workers. These gains are not automatic, however. They depend on whether employees are willing and able to integrate AI into their work.

Malaysia has adopted AI as a national priority. The Malaysia Digital Economy Blueprint (Economic Planning Unit, 2021) and the Malaysia National Artificial Intelligence Roadmap 2021–2025 (Ministry of Science, Technology and Innovation [MOSTI], 2021) both call for accelerated AI adoption across the public and private sectors, together with workforce upskilling. Many Malaysian organizations have invested in AI-enabled systems. Much less is known about whether Malaysian employees are psychologically and technically ready to use these systems, and whether that readiness improves their job performance. In practice, the gap between technology investment and workforce readiness is a common reason why digital transformation initiatives fail to deliver the expected returns (Jöhnk et al., 2021).

AI readiness is an individual-level concept. It refers to an employee's cognitive, affective and behavioural preparedness to accept, learn and use AI in their work. It draws on the broader literatures on technology readiness (Parasuraman & Colby, 2015), readiness for change (Rafferty et al., 2013) and AI literacy (Long & Magerko, 2020; Ng et al., 2021). Employees with high AI readiness are more likely to see AI as useful, to feel confident using it and to experiment with AI-assisted work processes. These dispositions are theoretically linked to higher task and contextual performance (Koopmans et al., 2014). Existing studies, however, have mainly examined organizational-level AI readiness (Jöhnk et al., 2021) or technology acceptance intentions (Venkatesh et al., 2012) rather than actual performance outcomes. Individual AI readiness as a direct predictor of employee performance remains under-studied, particularly in Southeast Asia.

The organizational context is also likely to shape whether individual readiness translates into performance. Organizational Support Theory holds that employees form global beliefs about how much their organization values their contributions and cares about their well-being, and that they reciprocate this support with greater effort and performance (Eisenberger et al., 2020; Kurtessis et al., 2017). In the context of AI adoption, organizational support takes concrete forms such as training, access to tools, time to learn, psychological safety to experiment and reassurance about job security. According to the Job Demands–Resources model (Bakker & Demerouti, 2017), such resources can amplify the positive effects of personal resources such as AI readiness. Without support, even ready employees may be unable to use AI productively, and they may experience AI as a threat rather than an opportunity (Kong et al., 2021; Tarafdar et al., 2019).

Against this background, this study has three objectives. It examines the level of AI readiness, perceived organizational support and employee performance among Malaysian employees. It determines the influence of AI readiness and perceived organizational support on employee performance. It tests whether perceived organizational support moderates the relationship between AI readiness and employee performance. The study contributes to the literature by treating AI readiness as an individual-level performance antecedent, by specifying the boundary role of organizational support, and by providing evidence from Malaysia, an emerging economy actively pursuing AI-driven transformation. Practically, the findings offer guidance to Malaysian HR practitioners and policymakers who are designing AI transition programmes.

Literature Review

2.1 AI Readiness

Readiness for technology has long been recognised as an important determinant of adoption behaviour. Parasuraman and Colby (2015) updated the Technology Readiness Index (TRI 2.0). They conceptualised readiness as the combination of enabling beliefs (optimism and innovativeness) and inhibiting beliefs (discomfort and insecurity) that together determine a person's propensity to embrace new technologies. AI readiness extends this idea to technologies that learn, predict and increasingly make decisions. At the organizational level, Jöhnk et al. (2021) identified strategic alignment, resources, knowledge, culture and data as the core factors of AI readiness. At the individual level, AI readiness overlaps with AI literacy: the competencies needed to understand, use, evaluate and critically reflect on AI applications (Long & Magerko, 2020; Ng et al., 2021). In this study, individual AI readiness is defined as an employee's knowledge of, confidence in, positive attitude towards and willingness to use AI in performing job tasks.

2.2 Employee Performance

Employee performance is multidimensional. Koopmans et al. (2011) systematically reviewed conceptual frameworks and identified task performance, contextual performance, adaptive performance and counterproductive work behaviour as its main dimensions. They later validated the Individual Work Performance Questionnaire (IWPQ) to measure these dimensions (Koopmans et al., 2014). In AI-enabled workplaces, adaptive performance has become increasingly important: the ability to learn new tools, adjust to changing work processes and solve novel problems. Raisch and Krakowski (2021) argue that AI can either automate or augment human work. Augmentation requires employees to work alongside AI systems and to exercise judgement over AI outputs, which places new performance demands on workers.

2.3 AI Readiness and Employee Performance

Several strands of evidence suggest that employees who are ready for AI perform better. Experimental studies show that AI assistance improves output speed and quality when workers actively and competently engage with the tools (Brynjolfsson et al., 2025; Noy & Zhang, 2023). Wijayati et al. (2022) found that artificial intelligence positively affected employee performance and work engagement in Indonesian organizations, and that change leadership moderated these effects. Tang et al. (2022) showed that the performance outcomes of working with intelligent machines depend on individual characteristics such as conscientiousness. The implication is that employee dispositions shape whether AI yields performance gains. Trust in AI, which is closely related to readiness, also determines whether employees rely on AI appropriately or reject its outputs (Glikson & Woolley, 2020). Employees high in AI readiness are therefore expected to use AI more effectively, to adapt more quickly and to perform better.

H1: AI readiness has a significant positive influence on employee performance.

2.4 Perceived Organizational Support

Perceived organizational support (POS) refers to employees' beliefs about the extent to which the organization values their contributions and cares about their well-being. Kurtessis et al. (2017) conducted a meta-analysis and confirmed that POS is associated with higher job performance, commitment and well-being, and with lower withdrawal behaviour. Eisenberger et al. (2020) explain these effects through social exchange and reciprocity. When employees feel supported, they feel obligated to help the organization reach its goals (Cropanzano et al., 2017). In AI adoption, POS is visible in training provision, tools and infrastructure, managerial encouragement and fair HR practices during technological change. Budhwar et al. (2022) and Chowdhury et al. (2023) stress that HRM plays a central role in building the human capabilities needed to extract value from AI.

H2: Perceived organizational support has a significant positive influence on employee performance.

2.5 The Moderating Role of Organizational Support

The Job Demands–Resources (JD-R) model proposes that job resources and personal resources interact to promote motivation and performance (Bakker & Demerouti, 2017). AI readiness can be viewed as a personal resource, and organizational support as a job resource. When both are high, employees have the capability and the opportunity to use AI productively. When support is low, ready employees may face barriers such as limited system access, insufficient training time or fear of job displacement. These barriers constrain the performance benefits of their readiness. Kong et al. (2021) found that employees' AI awareness can increase job burnout, and that this effect depends on contextual resources. Tarafdar et al. (2019) similarly show that technology can create either techno-eustress or techno-distress, depending on the resources available. Chatterjee et al. (2021) found that organizational and environmental conditions shape AI adoption success in manufacturing firms. On this basis, organizational support is expected to strengthen the relationship between AI readiness and performance.

H3: Perceived organizational support moderates the relationship between AI readiness and employee performance, such that the relationship is stronger when organizational support is high.

2.6 Research Gap and Conceptual Framework

Three gaps emerge from the review. First, most AI-readiness research focuses on organizations (Jöhnk et al., 2021) or on specific occupational groups, rather than on the general employee population. Second, studies linking AI to performance often measure AI use or exposure rather than employees' readiness (Wijayati et al., 2022). Third, evidence from Malaysia is scarce, despite the country's explicit national AI agenda (MOSTI, 2021). Recent debate on generative AI has also highlighted how quickly workplace expectations are changing (Dwivedi et al., 2023). This makes timely, context-specific evidence especially important. The conceptual framework of this study therefore positions AI readiness as the independent variable, employee performance as the dependent variable and perceived organizational support as the moderator (Figure 1).

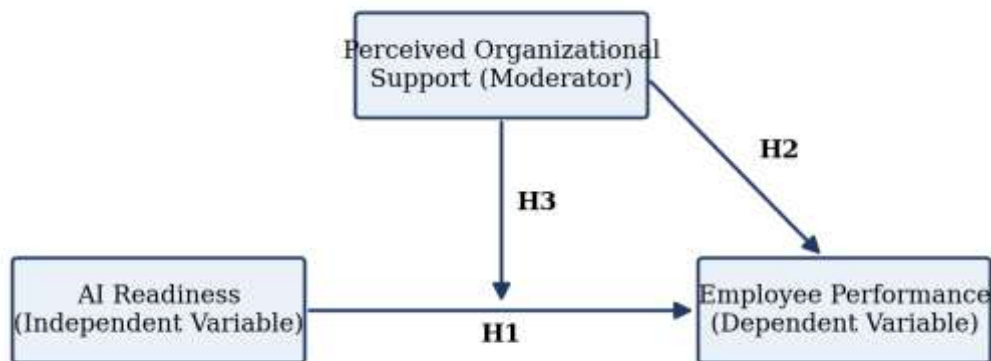


Figure 1. Conceptual framework of the study

Research Questions

- RQ1. What are the levels of AI readiness, perceived organizational support and employee performance among employees in Malaysia?
- RQ2. Does AI readiness significantly influence employee performance?
- RQ3. Does perceived organizational support significantly influence employee performance?
- RQ4. Does perceived organizational support moderate the relationship between AI readiness and employee performance?

Methodology

Research Design

The study used a quantitative, cross-sectional survey design. This design suits the testing of hypothesized relationships among latent constructs in a large sample, and allows the moderating role of organizational support to be examined statistically (Hair et al., 2019).

Population and Sample

The population comprised employees in Malaysian organizations who use, or are expected to use, AI-enabled tools in their work. The organizations came from the public sector, the private sector and government-linked companies (GLCs) in Peninsular Malaysia. The minimum sample size was estimated with G*Power 3.1 (Kang, 2021) for multiple regression with three predictors, a medium effect size ($f^2 = 0.15$), $\alpha = .05$ and power = .95. This gave a minimum of 119 respondents. To strengthen generalizability, and in line with conventional guidance for large populations, 384 usable responses were collected through purposive sampling. The questionnaire was distributed online through organizational HR contacts and professional networks.

Instrumentation

The questionnaire had four sections, and all items used a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The instrument was prepared in Bahasa Malaysia and English using back-translation. It was then reviewed by three content experts: two in human resource management and one in educational technology.

Table 1. Research instrument

Section	Construct	No. of items	Source (adapted from)
A	Demographic profile	5	Researcher-developed
B	AI Readiness (AIR)	8	Parasuraman & Colby (2015); Ng et al. (2021); Jöhnk et al. (2021)
C	Perceived Organizational Support (POS)	6	Eisenberger et al. (2020); Kurtessis et al. (2017)
D	Employee Performance (EP)	6	Koopmans et al. (2014)

Data Analysis

Data were analysed with IBM SPSS Statistics version 29. The analysis proceeded in six steps: (i) data screening for missing values, outliers and normality (skewness and kurtosis); (ii) construct validity using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity; (iii) reliability using Cronbach's alpha; (iv) a check for common method bias using Harman's single-factor test (Podsakoff et al., 2012); (v) descriptive statistics and Pearson correlation; and (vi) hierarchical moderated multiple regression with mean-centred predictors, followed by simple-slope analysis at ± 1 SD of POS (Hayes, 2022). Mean scores were interpreted as low (1.00–2.33), moderate (2.34–3.67) and high (3.68–5.00).

Findings

Demographic Profile

Table 2. Demographic profile of respondents (n = 384)

Variable	Category	Frequency	Percentage (%)
Gender	Male	169	44.0
	Female	215	56.0
Age	20–29 years	92	24.0
	30–39 years	140	36.5
	40–49 years	101	26.3
	50 years and above	51	13.3
Sector	Public sector	141	36.7
	Private sector	174	45.3
	Government-linked company (GLC)	69	18.0
Highest education	Diploma	79	20.6
	Bachelor's degree	201	52.3
	Master's degree	87	22.7
	Doctoral degree	17	4.4
Working experience	Less than 5 years	119	31.0
	5–10 years	132	34.4
	11–15 years	80	20.8
	More than 15 years	53	13.8

5.2 Validity, Reliability and Common Method Bias

Table 3. KMO, Bartlett's test and common method bias

Test	Result
Kaiser–Meyer–Olkin measure of sampling adequacy	.945
Bartlett's test of sphericity	$\chi^2(190) = 4163.83, p < .001$
Factors extracted (eigenvalue > 1)	3 (cumulative variance = 63.75%)
Harman's single factor (first factor variance)	40.12% (< 50%)

Table 4. Reliability analysis

Construct	No. of items	Cronbach's α	Interpretation
AI Readiness	8	.910	Excellent
Perceived Organizational Support	6	.902	Excellent
Employee Performance	6	.881	Good

The KMO value of .945 indicates excellent sampling adequacy. Bartlett's test was significant, so the data were suitable for factor analysis. Three factors emerged, matching the three constructs. The first factor accounted for 40.12% of the variance, below the 50% threshold, so common method bias is not a serious concern (Podsakoff et al., 2012). All Cronbach's alpha values exceeded .70 (Hair et al., 2019).

5.3 Normality

Table 5. Descriptive statistics and normality

Construct	Mean	SD	Skewness	Kurtosis	Level
AI Readiness	3.52	0.75	−0.253	−0.263	Moderate
Perceived Organizational Support	3.36	0.80	−0.159	−0.438	Moderate
Employee Performance	3.80	0.72	−0.347	−0.497	High

All skewness and kurtosis values fall within ± 2 , which indicates approximate normality (Hair et al., 2019).

5.4 RQ1: Levels of AI Readiness, Organizational Support and Performance

Table 6. Distribution of respondents by level

Construct	Low n (%)	Moderate n (%)	High n (%)
AI Readiness	22 (5.7)	193 (50.3)	169 (44.0)
Perceived Organizational Support	35 (9.1)	228 (59.4)	121 (31.5)
Employee Performance	8 (2.1)	163 (42.4)	213 (55.5)

Table 7. Item-level descriptives for AI Readiness

Item	Statement (sample wording)	Mean	SD
AIR1	I understand how AI tools can be applied in my job	3.55	0.94
AIR2	I feel confident using AI applications for work tasks	3.54	1.00
AIR3	I believe AI can improve the quality of my work	3.53	0.93
AIR4	I am willing to learn new AI tools introduced at work	3.58	0.92
AIR5	I can critically evaluate outputs produced by AI	3.49	1.00
AIR6	I feel comfortable when AI is integrated into work processes	3.51	0.94
AIR7	I understand the ethical risks of using AI at work	3.48	0.99
AIR8	I actively look for ways to use AI to work more efficiently	3.51	0.93

AI readiness was at a moderate level overall ($M = 3.52$). The highest-rated item was willingness to learn new AI tools ($M = 3.58$). The lowest-rated items concerned understanding the ethical risks of AI ($M = 3.48$) and critically evaluating AI outputs ($M = 3.49$). Perceived organizational support was also moderate ($M = 3.36$), and 9.1% of respondents reported low support. Employee performance was high ($M = 3.80$).

5.5 Correlation Analysis

Table 8. Pearson correlation matrix (n = 384)

Variable	M	SD	1	2	3
1. AI Readiness	3.52	0.75	(.910)		
2. Perceived Organizational Support	3.36	0.80	.434**	(.902)	
3. Employee Performance	3.80	0.72	.442**	.448**	(.881)

Note. ** $p < .01$ (two-tailed). Cronbach's alpha values are shown on the diagonal in parentheses.

All constructs were positively and moderately correlated. AI readiness correlated with employee performance at $r = .442$, and POS correlated with employee performance at $r = .448$ (both $p < .001$).

5.6 RQ2–RQ4: Hierarchical Moderated Regression

Table 9. Model summary

Model	R	R ²	Adj. R ²	SE	ΔR ²	F change	df1	df2	Sig. F change
1	.442	.195	.193	0.646	.195	92.52	1	382	< .001
2	.525	.276	.272	0.614	.081	42.70	1	381	< .001
3	.540	.291	.286	0.608	.015	8.11	1	380	.005

Note. Model 1: AI Readiness. Model 2: + Perceived Organizational Support. Model 3: + AI Readiness × POS. Durbin–Watson = 1.905.

Table 10. ANOVA

Model	df (regression, residual)	F	Sig.
1	1, 382	92.52	< .001
2	2, 381	72.66	< .001
3	3, 380	52.05	< .001

Table 11. Regression coefficients (dependent variable: Employee Performance)

Model	Predictor	B	SE	β	t	Sig.	VIF
1	(Constant)	3.796	0.033		115.12	< .001	
	AI Readiness	0.424	0.044	.442	9.62	< .001	1.000
2	(Constant)	3.796	0.031		121.24	< .001	
	AI Readiness	0.292	0.046	.304	6.29	< .001	1.232
	POS	0.285	0.044	.316	6.53	< .001	1.232
3	(Constant)	3.761	0.033		112.93	< .001	
	AI Readiness	0.314	0.047	.327	6.73	< .001	1.266
	POS	0.292	0.043	.324	6.76	< .001	1.236
	AI Readiness × POS	0.134	0.047	.126	2.85	.005	1.049

Note. Predictors were mean-centred before the interaction term was computed. 95% CI for the interaction B = [0.041, 0.226].

Table 12. Conditional effect of AI Readiness on Employee Performance at levels of POS

Level of POS	POS (centred)	Effect (B)	SE	t	p	95% CI
Low (−1 SD)	−0.798	0.208	0.055	3.79	< .001	[0.100, 0.315]
Mean	0.000	0.314	0.047	6.73	< .001	[0.222, 0.406]
High (+1 SD)	+0.798	0.421	0.064	6.53	< .001	[0.294, 0.547]

Table 13. Summary of hypothesis testing

Hypothesis	Path	β	p	Decision
H1	AI Readiness → Employee Performance	.327	< .001	Supported
H2	POS → Employee Performance	.324	< .001	Supported
H3	AI Readiness × POS → Employee Performance	.126	.005	Supported

AI readiness alone explained 19.5% of the variance in employee performance (Model 1). Adding POS explained a further 8.1% (Model 2). The interaction term added another 1.5% (Model 3), which was significant, $F_{\text{change}}(1, 380) = 8.11, p = .005$. The final model explained 29.1% of the variance. All VIF values were below 1.3 and the Durbin–Watson statistic was 1.905, so multicollinearity and autocorrelation were not concerns. The simple-slope analysis shows that the effect of AI readiness on performance roughly doubles from low POS ($B = 0.208$) to high POS ($B = 0.421$).

Discussion

The first finding is that Malaysian employees reported moderate AI readiness. Willingness to learn AI tools was relatively strong, but the ability to critically evaluate AI outputs and to understand the ethical risks of AI was weaker. This pattern fits the AI literacy literature, which separates the ability to use AI from the ability to understand and critique it (Long & Magerko, 2020; Ng et al., 2021). It suggests that Malaysian employees are motivationally open to AI but not yet fully equipped to use it critically. Organizational support was also only moderate. This points to a gap between national ambitions for AI adoption (MOSTI, 2021) and the support employees actually experience at work.

The second finding supports H1: AI readiness significantly predicts employee performance. This agrees with experimental evidence that AI improves productivity when workers engage with it competently (Brynjolfsson et al., 2025; Noy & Zhang, 2023). It also agrees with Wijayati et al. (2022), who found positive effects of AI on employee performance in Indonesia, a neighbouring context. Theoretically, the finding supports the view that readiness, as a combination of optimism, confidence and competence (Parasuraman & Colby, 2015), is a personal resource that enables adaptive and task performance (Koopmans et al., 2011). Employees who are ready for AI are better placed to use AI for augmentation rather than to resist it (Raisch & Krakowski, 2021).

The third finding supports H2: perceived organizational support predicts employee performance independently of AI readiness. This is consistent with meta-analytic evidence (Kurtessis et al., 2017) and with social exchange explanations of POS (Cropanzano et al., 2017; Eisenberger et al., 2020). During AI-driven change, employees who feel valued and cared for are likely to repay the organization with greater effort, even while their work processes are being disrupted.

The fourth and most important finding supports H3: organizational support strengthens the relationship between AI readiness and performance. The effect of readiness at high POS was about twice as large as at low POS. This supports the JD-R proposition that personal and job resources interact (Bakker & Demerouti, 2017). A ready employee in an unsupportive organization gains relatively little from that readiness, while the same employee in a supportive organization gains considerably more. The result is consistent with evidence that contextual conditions shape whether AI produces eustress or distress (Kong et al., 2021; Tarafdar et al., 2019), and with arguments that HRM is central to realising the value of AI (Budhwar et al., 2022; Chowdhury et al., 2023). The interaction explained a modest 1.5% of additional variance. Effects of this size are common for interactions in field research and are practically meaningful.

Conclusion

This study examined the influence of AI readiness on employee performance and the moderating role of perceived organizational support among 384 Malaysian employees. AI readiness and organizational support both positively predicted employee performance. Organizational support also strengthened the effect of AI readiness on performance. The central conclusion is that AI-related performance gains are not only a matter of individual preparedness. They emerge when prepared employees work in organizations that actively support their AI journey. Theoretically, the study extends Organizational

Support Theory and the JD-R model to AI adoption and establishes AI readiness as an individual-level antecedent of performance. Empirically, it adds evidence from Malaysia, an under-represented context in AI workforce research.

8. Recommendations

8.1 For Organizations and HR Practitioners

- **Build AI readiness systematically.** Offer structured AI literacy programmes that cover critical evaluation of AI outputs and AI ethics, not only tool operation, since these were the weakest areas.
- **Make organizational support visible.** Provide protected learning time, access to licensed AI tools, internal help channels and clear AI usage guidelines.
- **Reduce job-security anxiety.** Communicate clearly that AI is intended to augment roles, and involve employees in redesigning AI-enabled work processes.
- **Align AI investment with people investment.** Treat training and support as part of the cost of every AI implementation, not as optional extras.

8.2 For Policymakers

- Link national AI initiatives, such as the National AI Roadmap and MyDIGITAL, to workplace-level upskilling incentives, especially for SMEs and the public sector.
- Develop national AI literacy competency standards that include critical and ethical dimensions.

8.3 For Future Research

- Use longitudinal or experimental designs to establish causality.
- Use supervisor-rated or objective performance measures to reduce self-report bias.
- Test other moderators and mediators, such as leadership support, trust in AI (Glikson & Woolley, 2020), technostress and work engagement.
- Compare sectors (public, private and GLC) and regions (Peninsular Malaysia, Sabah and Sarawak) using multi-group analysis or PLS-SEM.
- Examine generative AI use specifically, given how rapidly it is changing (Dwivedi et al., 2023).

8.4 Limitations

The study relied on cross-sectional, self-reported data and purposive sampling. This limits causal inference and generalisability. Harman's test indicated no serious common method bias, but future studies should use multi-source data.

Co-Author Contribution

Author 1 carried out the fieldwork, prepared the literature review and overlooked the whole article's write up. Authors 2, 3 wrote the research methodology and did the data entry. Authors 4, 5, 6 carried out the statistical analysis and interpretation of the results.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

Acknowledgement

Special thanks are extended to the participating organization for their cooperation and support throughout the research process

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Data Availability Statement: All relevant data are within the manuscript and its [Supporting Information](#) files.