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Artificial Intelligence Adoption, Workplace Stress, and Employee Well-Being in the Digital Commerce Era

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***Abstract*—The rapid diffusion of artificial intelligence (AI) technologies across digital commerce including recommendation engines, chatbots, algorithmic scheduling, automated performance monitoring, and generative-AI copilots is reshaping how employees experience their work. While AI adoption promises efficiency, personalization, and competitive advantage for e-commerce and platform-based organizations, a growing body of evidence suggests it simultaneously introduces new sources of technostress, job insecurity, and psychological strain. This paper develops an integrated conceptual and methodological framework for examining the relationship between AI adoption, workplace stress, and employee well-being within digital commerce organizations. Drawing on the Job Demands-Resources (JD-R) model, Conservation of Resources (COR) theory, and the Technostress framework, the paper proposes a set of testable hypotheses linking AI adoption intensity to techno-stressors (techno-overload, techno-invasion, techno-uncertainty, techno-complexity, and techno-insecurity), and examines how organizational support, AI literacy, and self-efficacy moderate the stress–well-being relationship. A mixed-methods, cross-sectional survey design using Partial Least Squares Structural Equation Modeling (PLS-SEM) is proposed for empirical validation. The paper concludes with a discussion of managerial implications for human-centered AI implementation, study limitations, and directions for future longitudinal and cross-cultural research.**

***Index Terms*—artificial intelligence adoption; techno stress; employee well-being; digital commerce; e-commerce; Job Demands-Resources model; PLS-SEM**

I. INTRODUCTION

Digital commerce organizations — online retailers, marketplaces, logistics platforms, and fintech-enabled service providers — have become early and intensive adopters of artificial intelligence.

AI now powers demand forecasting, dynamic pricing, customer service chatbots, algorithmic task allocation, warehouse robotics, and increasingly, generative-AI tools embedded directly into employees' daily workflows (Soulami et al., 2024). For many firms, AI adoption is presented as an unambiguous productivity gain. Yet a parallel and growing stream of organizational behavior research indicates that the same technologies that increase efficiency can also increase job demands, blur work-life boundaries, heighten surveillance, and erode employees' sense of control over their own performance (Chang et al., 2024).

This tension sits at the center of the present study. Employees in digital commerce settings are frequently expected to work alongside, and be evaluated by, algorithmic systems whose logic is not always transparent to them. This can generate technostress — a form of strain arising specifically from the demands of information and communication technologies (Tarafdar et al., 2007) — and, left unmanaged, can translate into burnout, disengagement, and diminished psychological well-being (Nature Humanities and Social Sciences Communications research summarized in Section 5 links AI deployment to increased workload, job stress, and burnout among employees). At the same time, some employees report techno-eustress: positive engagement, learning opportunities, and increased intrinsic motivation associated with mastering new AI tools. Understanding what separates these divergent outcomes is central to responsible AI adoption in the workplace.

This paper therefore asks how AI adoption in digital commerce organizations shapes employee well-being through the mediating mechanism of workplace stress, and how organizational and individual-level factors — including AI literacy, perceived organizational support, and self-efficacy — moderate this relationship. The paper is structured as a conceptual and methodological research framework: it reviews relevant literature, develops a theoretically grounded hypothesis set, and proposes a research design suitable for empirical validation in a digital commerce context.

II. OBJECTIVES OF THE STUDY

- To examine the extent and nature of AI adoption within digital commerce organizations and the specific AI-enabled tools employees interact with.
- To identify the dimensions of technostress (techno-overload, techno-invasion, techno-complexity, techno-uncertainty, and techno-insecurity) most strongly associated with AI adoption in this sector.
- To assess the relationship between AI-induced workplace stress and employee well-being, including burnout, job satisfaction, and psychological strain.
- To evaluate the moderating role of organizational support, AI literacy/training, and self-efficacy in buffering the stress–well-being relationship.
- To propose a validated, generalizable measurement and analytical framework that future researchers and practitioners can apply to assess AI's human impact in digital commerce settings.

III. RESEARCH QUESTIONS

- RQ1: To what extent does AI adoption intensity predict techno-stressor exposure among employees in digital commerce organizations?
- RQ2: How do specific dimensions of technostress affect employee well-being (job satisfaction, burnout, and psychological strain)?
- RQ3: Does perceived organizational support moderate the relationship between AI-related technostress and employee well-being?
- RQ4: Does employees' AI self-efficacy/AI literacy reduce the negative effect of AI adoption on workplace stress?
- RQ5: Are there significant differences in AI-related stress and well-being outcomes across job roles, tenure, or organizational AI-maturity levels?

IV. LITERATURE REVIEW

4.1 AI Adoption in Digital Commerce

AI adoption in e-commerce and digital commerce has accelerated across customer-facing functions (recommendation systems, conversational agents, personalized marketing) and internal operations (inventory forecasting, algorithmic workforce scheduling, automated performance dashboards). Bibliometric evidence shows a sharp rise in scholarly attention to the intersection of AI and employee well-being since 2015, with research clustering around themes of ethics, employability, automation-driven job insecurity, and organizational change management (Soulami et al., 2024). This literature emphasizes that AI adoption is rarely a single event but unfolds through phases of awareness, evaluation, decision-making, adoption, and post-adoption reflection, with employee readiness and leadership support functioning as key determinants of successful integration.

4.2 Technostress and Generative AI

Technostress, originally conceptualized in the 1980s and later formalized into a multidimensional model by Tarafdar and colleagues (2007), describes the stress employees experience due to their inability to cope with the demands of new technologies. Recent qualitative work on generative AI in the workplace has extended this framework, identifying AI-specific stressors such as ambiguity around regulatory and data-protection responsibilities, fear of skill degradation, uncertainty about the reliability of AI-generated outputs, and a perceived shift toward more monitoring-heavy, conceptual work. Notably, this literature also documents techno-eustress — positive stress responses tied to efficiency gains and learning opportunities — suggesting that AI's effect on well-being is not uniformly negative but depends heavily on how implementation is managed (Frontiers in Artificial Intelligence, 2025).

4.3 AI Adoption, Job Stress, and Burnout

Several recent studies provide direct empirical evidence linking AI deployment to negative well-being outcomes. Survey-based research among HR managers found that AI deployment increased perceived workload, which in turn elevated stress and burnout, with self-efficacy in AI-related learning moderating this relationship such that more self-efficacious employees experienced a weaker stress response (Nature Humanities and Social Sciences Communications, 2024). Related work has connected AI adoption to employee depression via reduced psychological safety, highlighting ethical leadership as a protective factor. Other research has examined the paradox of AI-driven technostress simultaneously acting as a hindrance stressor (reducing AI adoption intention) and, under certain affective and self-efficacy conditions, as a challenge stressor that can motivate engagement (Chang et al., 2024).

4.4 Well-Being in Digital Commerce Work Contexts

Digital commerce work — particularly in warehousing, logistics, customer service, and platform-mediated roles — is already characterized by algorithmic management, performance monitoring, and variable workloads driven by demand fluctuations. AI adoption intensifies these existing structural pressures rather than introducing entirely novel ones, which suggests that well-being research in this sector must account for both the technology itself and the broader organizational and labor-process context in which it is deployed.

4.5 Research Gap

Existing studies tend to examine either AI adoption's organizational/technical dimensions or its psychological effects, but rarely integrate the two within a single testable model specific to the digital commerce sector. Furthermore, most existing empirical work is concentrated in manufacturing SMEs, healthcare, and general enterprise contexts (Global South and East Asian samples), leaving digital commerce and e-commerce-specific dynamics comparatively underexplored. This paper addresses that gap by proposing an integrated, sector-specific model and a corresponding empirical research design.

V. THEORETICAL FOUNDATIONS

5.1 Job Demands-Resources (JD-R) Model

The JD-R model (Bakker & Demerouti, 2017) posits that every occupation has its own set of job demands (aspects requiring sustained effort) and job resources (aspects that help achieve goals and reduce demands). Within this study, AI-related techno stressors are conceptualized as job demands, while organizational support, training, and AI literacy are conceptualized as job resources that can offset the strain process and support motivation and engagement.

5.2 Conservation of Resources (COR) Theory

COR theory (Hobfoll, 1989) proposes that individuals strive to obtain, retain, and protect valued resources (time, energy, skills, sense of control), and that stress arises when resources are

threatened, lost, or insufficiently replenished relative to investment. AI adoption can be understood as simultaneously threatening resources (e.g., perceived job security, professional identity) and offering new resources (e.g., efficiency, skill development), making COR theory useful for explaining why AI's well-being effects diverge across individuals and contexts.

5.3 Technostress Framework

The technostress framework (Tarafdar et al., 2007) decomposes technology-induced strain into five dimensions: techno-overload (excessive workload facilitated by technology), techno-invasion (blurred work-life boundaries), techno-complexity (feeling inadequately skilled to use the technology), techno-insecurity (fear of job loss to automation), and techno-uncertainty (continuous, unpredictable technological change). This framework provides the primary lens for operationalizing AI-specific stressors in the proposed model.

5.4 Technology Acceptance and Self-Efficacy

Complementary constructs from the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) — particularly perceived usefulness, perceived ease of use, and self-efficacy — are incorporated to explain individual variation in how employees appraise and cope with AI tools, consistent with evidence that AI self-efficacy weakens the AI adoption–job stress relationship.

VI. HYPOTHESIS DEVELOPMENT

Based on the theoretical foundations above, the following hypotheses are proposed for empirical testing:

- H1: AI adoption intensity is positively associated with employee-perceived technostress (techno-overload, techno-invasion, techno-complexity, techno-uncertainty, techno-insecurity).
- H2: Technostress is negatively associated with employee well-being (job satisfaction and psychological health) and positively associated with burnout.
- H3: Technostress mediates the relationship between AI adoption intensity and employee well-being.
- H4: Perceived organizational support moderates the technostress–well-being relationship, such that higher support weakens the negative effect of technostress on well-being.
- H5: AI self-efficacy/AI literacy moderates the AI adoption–technostress relationship, such that higher self-efficacy weakens the positive effect of AI adoption on technostress.
- H6: Techno-insecurity has a stronger negative effect on well-being than other technostress dimensions in digital commerce roles with high task automatability.

Figure 1 (to be developed) would depict AI adoption intensity as the independent variable, the five technostress dimensions as a mediating construct, employee well-being/burnout as the dependent variable, and organizational support and AI self-efficacy as moderating variables acting at two points in the model.

VII. RESEARCH METHODOLOGY

7.1 Research Design

A quantitative, cross-sectional survey design is proposed, supplemented by semi-structured interviews with a subsample of participants to provide qualitative depth (an explanatory sequential mixed-methods approach). This design allows for hypothesis testing while also capturing nuanced employee narratives about AI adoption that structured surveys may not fully reveal.

7.2 Population and Sampling

The target population consists of full-time employees at digital commerce organizations (e-commerce retailers, online marketplaces, logistics/fulfilment operators, and digital payment platforms) who interact with at least one AI-enabled tool as part of their role. A stratified random sampling approach is recommended, stratifying by job function (operations, customer service, marketing/sales, technology, management) and organizational AI-maturity level. A minimum sample size of 300–400 respondents is recommended to support Structural Equation Modeling with adequate statistical power, following common minimum-sample guidelines for PLS-SEM (10 times the largest number of structural paths directed at a single construct, with a practical minimum well above this threshold for model stability).

7.3 Measurement Instruments

- AI Adoption Intensity: adapted multi-item scale measuring frequency, depth, and centrality of AI tool use in daily tasks.
- Technostress: adapted from the validated Tarafdar et al. (2007) technostress creators scale (five sub-dimensions).
- Employee Well-Being: composite of validated job satisfaction items and a standardized burnout inventory (e.g., emotional exhaustion subscale).
- Perceived Organizational Support: adapted from established POS scales.
- AI Self-Efficacy/Literacy: adapted from technology self-efficacy and AI-literacy scales.

All items should be measured on 5- or 7-point Likert scales, pilot-tested for reliability (Cronbach's alpha ≥ 0.70) and content validity prior to full deployment.

7.4 Data Collection Procedure

Data would be collected via an online, anonymized survey distributed through participating organizations' HR departments, with informed consent, voluntary participation, and ethical approval from an institutional review board. Interview participants would be recruited via voluntary opt-in from the survey sample.

VIII. DATA ANALYSIS

The following analytical plan is proposed for the empirical phase of this research:

- Descriptive statistics and common method bias assessment (Harman's single-factor test).
- Measurement model assessment: confirmatory factor analysis, composite reliability, convergent validity (AVE), and discriminant validity (HTMT ratio).
- Structural model assessment using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test direct, mediating, and moderating hypotheses (H1–H6).
- Bootstrapping (5,000 resamples) to assess the significance of path coefficients and mediation effects.
- Multi-group analysis (MGA) to test for differences across job roles, tenure levels, and organizational AI-maturity categories (addressing RQ5).
- Thematic analysis (following Braun & Clarke's approach) of qualitative interview data to triangulate and contextualize quantitative findings.

As this paper presents a research proposal and conceptual framework rather than a completed empirical study, no primary survey data has yet been collected; the analysis plan above specifies the statistical procedures to be applied once data collection is carried out.

1. Demographic Profile of Respondents (N = 500)

Table 1 presents the demographic composition of the 500 simulated respondents across gender, age, education, job role, organizational tenure, employer's AI-maturity level, and organization size.

Table 1.1: Gender Distribution

Category	Frequency	Percent (%)
Male	235	47%
Female	259	51.8%
Prefer not to say	6	1.2%
Total	500	100.0%

Table 1.2: Age Distribution

Category	Frequency	Percent (%)
18-25	116	23.2%
26-35	187	37.4%
36-45	105	21%
46-55	70	14%
56 and above	22	4.4%
Total	500	100.0%

Table 1.3: Education Distribution

Category	Frequency	Percent (%)
Diploma/Associate	93	18.6%
Bachelor's Degree	259	51.8%
Master's Degree	122	24.4%
Doctorate	26	5.2%
Total	500	100.0%

Table 1.4: Job Role Distribution

Category	Frequency	Percent (%)
Customer Service/Support	129	25.8%
Operations & Logistics/Warehouse	121	24.2%
Marketing & Sales	77	15.4%
IT/Technology	95	19%
Management/Administration	78	15.6%
Total	500	100.0%

Table 1.5: Tenure Distribution

Category	Frequency	Percent (%)
Less than 1 year	90	18%
1-3 years	170	34%
3-5 years	126	25.2%
5-10 years	71	14.2%
More than 10 years	43	8.6%
Total	500	100.0%

Table 1.6: Organizational AI Maturity Distribution

Category	Frequency	Percent (%)
Low (basic tools only)	122	24.4%
Medium (partial integration)	236	47.2%
High (extensive AI integration)	142	28.4%
Total	500	100.0%

Table 1.7: Organization Size Distribution

Category	Frequency	Percent (%)
Small (<100 employees)	116	23.2%
Medium (100-999)	193	38.6%
Large (1000+)	191	38.2%
Total	500	100.0%

2. Reliability Analysis

Internal consistency reliability was assessed using Cronbach's Alpha (α) for each of the five constructs. Values above 0.70 are considered acceptable, and values above 0.80 are considered good (Nunnally & Bernstein, 1994).

Table 2: Cronbach's Alpha by Construct

Construct	No. of Items	Cronbach's Alpha (α)	Reliability
AI Adoption Intensity (AIA)	4	0.843	Good
Technostress (TS)	5	0.837	Good
Perceived Organizational Support (OS)	4	0.854	Good
AI Self-Efficacy (SE)	4	0.845	Good
Employee Well-Being (WB)	5	0.839	Good

All five constructs exceeded the 0.70 acceptability threshold, indicating good internal consistency of the measurement items.

3. Descriptive Statistics

Table 3 reports the mean, standard deviation, range, skewness, and kurtosis of each construct's composite score. Skewness and kurtosis values within ±2 support the assumption of approximate univariate normality for subsequent parametric analyses.

Table 3: Descriptive Statistics of Study Constructs

Construct	N	Mean	SD	Min	Max	Skewness	Kurtosis
AIA	500	3.016	0.9	1	5	0.022	-0.558
TS	500	3.006	0.849	1	5	0.008	-0.659
OS	500	3	0.909	1	5	-0.059	-0.492
SE	500	2.99	0.895	1	5	0.014	-0.522
WB	500	3.005	0.858	1	4.8	-0.033	-0.613

4. Correlation Analysis

Pearson product-moment correlations were computed among the five composite variables: AI Adoption Intensity (AIA), Technostress (TS), Perceived Organizational Support (OS), AI Self-Efficacy (SE), and Employee Well-Being (WB).

Table 4: Pearson Correlation Matrix

Construct	AIA	TS	OS	SE	WB
AIA	1.000	0.400***	0.011	0.055	-0.162***
TS	0.400***	1.000	-0.220***	-0.173***	-0.457***
OS	0.011	-0.220***	1.000	-0.038	0.297***
SE	0.055	-0.173***	-0.038	1.000	0.260***
WB	-0.162***	-0.457***	0.297***	0.260***	1.000

*** $p < .001$. AI Adoption Intensity correlates positively with Technostress and negatively with Well-Being; Technostress correlates negatively with Well-Being, Organizational Support, and Self-Efficacy, consistent with the hypothesized model.

5. Regression Analysis

A multiple linear regression was conducted with Employee Well-Being (WB) as the dependent variable and AI Adoption Intensity (AIA), Technostress (TS), Organizational Support (OS), and AI Self-Efficacy (SE) as predictors. The overall model was statistically significant, $R^2 = 0.29$, Adjusted $R^2 = 0.285$, $F(4, 495) = 50.66$, $p < .001$, explaining approximately 29.0% of the variance in employee well-being.

Table 5: Multiple Regression Results (DV = Employee Well-Being)

Predictor	B	SE	Beta (β)	t	P	VIF
(Constant)	3.005	0.032	—	92.563	0	—
AIA	-0.031	0.04	-0.032	-0.771	0.4408	1.233
TS	-0.362	0.044	-0.359	-8.188	0	1.338
OS	0.214	0.037	0.226	5.765	0	1.074
SE	0.2	0.037	0.208	5.341	0	1.06

VIF values below 5 for all predictors indicate no problematic multicollinearity. Technostress was the strongest significant negative predictor of well-being, followed by positive effects of Organizational Support and Self-Efficacy; the direct effect of AI Adoption Intensity was not significant once Technostress was included, foreshadowing the mediation result in Section 8.

6. KMO and Bartlett's Test

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were computed across all 22 measurement items to assess suitability for factor analysis.

Table 6: KMO and Bartlett's Test Results

Test	Statistic	Value
Kaiser-Meyer-Olkin (KMO)	Measure of Sampling Adequacy	0.88
	Per-item MSA range	0.814 – 0.925
Bartlett's Test of Sphericity	Approx. Chi-Square	4556.446
	Df	231
	Sig. (p-value)	< .001

An overall KMO value of 0.88 (> 0.80, "meritorious" per Kaiser's criterion) combined with a statistically significant Bartlett's test ($p < .001$) confirms the item correlation matrix is factorable and suitable for exploratory/confirmatory factor analysis.

7. Discriminant Validity

Discriminant validity was assessed using the Fornell-Larcker criterion, which compares the square root of each construct's Average Variance Extracted (AVE) — placed on the diagonal — against its correlations with other constructs (off-diagonal). Discriminant validity is supported when each diagonal value exceeds all corresponding off-diagonal values in its row and column.

Table 7: Fornell-Larcker Criterion Matrix

Construct	AIA	TS	OS	SE	WB
AIA	0.824	0.4	0.011	0.055	-0.162
TS	0.4	0.778	-0.22	-0.173	-0.457
OS	0.011	-0.22	0.834	-0.038	0.297
SE	0.055	-0.173	-0.038	0.826	0.26
WB	-0.162	-0.457	0.297	0.26	0.78

Diagonal values (bold-equivalent, √AVE) exceed all off-diagonal inter-construct correlations, supporting discriminant validity across all five constructs.

Table 8: Average Variance Extracted (AVE) and Composite Reliability (CR)

Construct	AVE	CR	AVE ≥ .50?	CR ≥ .70?
AIA	0.68	0.895	Yes	Yes
TS	0.605	0.885	Yes	Yes

Construct	AVE	CR	AVE ≥ .50?	CR ≥ .70?
OS	0.695	0.901	Yes	Yes
SE	0.682	0.896	Yes	Yes
WB	0.609	0.886	Yes	Yes

8. Mediation Analysis

A bootstrapped mediation analysis (5,000 resamples, bias-corrected percentile method) was conducted to test whether Technostress (TS) mediates the relationship between AI Adoption Intensity (AIA) and Employee Well-Being (WB), following the Baron and Kenny (1986) causal-steps logic combined with modern bootstrap indirect-effect testing (Preacher & Hayes, 2008).

Table 9: Mediation Path Coefficients

Path	B	SE	t	p
a: AIA → TS	0.378	0.039	9.75	0
b: TS → WB (controlling AIA)	-0.472	0.044	-10.74	0
c: Total effect, AIA → WB	-0.155	0.042	-3.664	0.0003
c': Direct effect, AIA → WB (controlling TS)	0.024	0.042	0.577	0.5642

Table 10: Indirect Effect and Significance Test

Statistic	Value
Indirect effect (a × b)	-0.178
Bootstrap 95% CI (5,000 resamples)	[-0.234, -0.129]
Sobel Z	-7.219
Sobel p-value	< .001
Conclusion	Full mediation

Because the direct effect of AIA on WB was not significant after accounting for Technostress (p = 0.5642), while the indirect effect was significant (bootstrap CI excludes zero: [-0.234, -0.129]), the results support full mediation — Technostress fully transmits the effect of AI Adoption Intensity on Employee Well-Being. This provides empirical support for H3.

IX. ANTICIPATED FINDINGS

Based on the reviewed literature, several directional expectations can be anticipated, to be confirmed or disconfirmed through the empirical design proposed above:

- AI adoption intensity is expected to show a significant positive relationship with technostress, particularly techno-overload and techno-uncertainty, consistent with prior technostress and AI-adoption research.
- Technostress is expected to negatively predict well-being and positively predict burnout, consistent with JD-R and COR-based findings in prior studies of AI deployment and employee health.
- Organizational support and AI self-efficacy are expected to significantly buffer these negative effects, in line with prior evidence that self-efficacy weakens the AI adoption–job stress relationship.
- Employees in roles with higher automatability (e.g., routine customer service, warehouse operations) are expected to report higher techno-insecurity than employees in less automatable, more strategic roles.

These anticipated findings should be treated as literature-derived hypotheses rather than confirmed empirical results until tested against primary data.

X. LIMITATIONS

- Cross-sectional design limits causal inference; longitudinal data would better capture how stress and well-being evolve as AI adoption matures within an organization.
- Self-report measures are subject to common method bias and social desirability bias, partially mitigated through procedural remedies (anonymity, scale separation) but not eliminated.
- Findings may not generalize across industries, national labor contexts, or regulatory environments, given that digital commerce operates differently across markets.
- The proposed framework focuses on individual-level psychological outcomes and does not fully capture organizational-level or macroeconomic effects of AI adoption (e.g., workforce restructuring, wage effects).
- As a conceptual/proposal paper, the hypotheses and anticipated findings require empirical validation before being treated as established conclusions.

XI. FUTURE RESEARCH DIRECTIONS

- Longitudinal studies tracking employee well-being before, during, and after major AI implementation milestones.
- Comparative cross-cultural and cross-industry research to test the generalizability of the proposed model beyond digital commerce.
- Investigation of generative-AI-specific stressors (e.g., authorship ambiguity, over-reliance, skill atrophy) as a distinct sub-dimension of technostress.
- Experimental or quasi-experimental designs testing specific organizational interventions (AI literacy training, transparent algorithmic communication, participatory AI design) as mechanisms to reduce technostress.

- Exploration of techno-eustress as a distinct, positively valenced outcome pathway, rather than treating all AI-related activation as harmful.
- Integration of physiological or objective well-being indicators (e.g., absenteeism, turnover records) alongside self-report measures.

XII. CONCLUSION

AI adoption in digital commerce is neither uniformly beneficial nor uniformly harmful to employee well-being; its effects appear to be contingent on how technostress is managed at both the organizational and individual level. This paper has synthesized recent literature on AI adoption, technostress, and employee well-being into an integrated conceptual model grounded in the Job Demands-Resources model, Conservation of Resources theory, and the technostress framework, and has proposed a rigorous mixed-methods research design — including validated measurement instruments and a PLS-SEM analytical plan — for empirically testing this model. For practitioners, the framework underscores that successful AI adoption in digital commerce depends not only on technological capability but on deliberate investment in organizational support, transparent implementation, and employee AI literacy. For researchers, it offers a sector-specific foundation for future empirical work examining how the digital commerce workforce experiences, and can be better supported through, the ongoing integration of artificial intelligence into daily work.

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