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Digital Talent Management and Logistics Resilience: The Mediating Role of Workforce Agility and the Moderating Effect of AI Adoption

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Abstract. Logistics resilience depends not only on technology but also on the workforce capabilities through which operational responses are executed. Drawing on the resource-based view and dynamic capabilities theory, this study examines how digital talent management influences logistics resilience through workforce agility and whether AI adoption strengthens the workforce-agility-to-resilience link. Survey data from 382 logistics and operations managers were analyzed using hierarchical regression and conditional process analysis. Digital talent management positively predicts workforce agility ($\beta = 0.589$, $p < 0.001$), while workforce agility positively predicts logistics resilience. The workforce agility–logistics resilience relationship is significantly moderated by AI adoption ($\beta = 0.195$, $p < 0.001$). Coefficient-product conditional indirect-effect point estimates are 0.086 at low AI adoption, 0.201 at the sample mean, and 0.316 at high AI adoption. The direct effect of digital talent management remains marginal after workforce agility is included ($\beta = 0.113$, $p = 0.060$). The findings place workforce agility at the center of the digital talent–resilience pathway and show that the strength of this pathway varies with AI adoption.

Keywords: Digital talent management; Workforce agility; Artificial intelligence adoption; Logistics resilience; Moderated mediation

1. Introduction

1.1. Research Background

Over the past few years, logistics systems around the world have faced a series of serious shocks, including demand fluctuations caused by the pandemic, labor shortages, and disruptions in freight networks resulting from geopolitical tensions. As a result, logistics resilience, defined as the ability of logistics systems to anticipate, absorb, and recover from disruptions, has become an important research focus worldwide (Christopher & Peck, 2004). Existing research has mainly emphasized technological enablers of resilience, including digital visibility platforms, predictive analytics, and increasingly artificial intelligence-based decision-support systems (Belhadi et al., 2021; Modgil, Singh, & Hannibal, 2022). However, logistics operations ultimately depend on human resources, and recent human resource management research suggests that workforce skills, adaptability, and rapid reconfiguration capabilities represent important but relatively underexplored mechanisms for strengthening organizational resilience (Sherehiy & Karwowski, 2014).

Digital talent management refers to the systematic use of digital technologies, talent analytics, and intelligent platforms to identify, recruit, develop, deploy, and retain strategically important employees to support organizational competitiveness and digital transformation (Tarique & Schuler, 2010). Through digital tools, organizations can identify employee skill gaps and flexibly allocate or retrain employees according to changing work requirements. However, whether and how this capability improves logistics resilience remains unclear (Kane et al., 2017). One possible mechanism is through enhancing workforce agility, which enables employees to adapt rapidly to changing tasks and operational conditions (Breu et al., 2002). Furthermore, the extent to which this mechanism operates may depend on organizational AI adoption, because artificial intelligence systems can provide employees with timely analytical support and improve their ability to respond to environmental changes.

The importance of clarifying this mechanism is further highlighted by the fact that logistics organizations increasingly need to invest simultaneously in two forms of digital capability: one focusing on human resources (digital talent management) and the other focusing on technology infrastructure (AI adoption). However, limited guidance exists regarding how these investments should be coordinated. The empirical issue concerns whether digital talent management contributes to resilience and whether the association varies with parallel investments in AI-based decision-support capabilities. Existing research has generally examined these two capabilities separately, with human resource management studies emphasizing talent digitalization and operations management studies focusing on AI-enabled resilience improvement, while limited empirical research has integrated these perspectives (Vadithe & Kesari, 2025). This study develops a moderated mediation model to examine how digital talent management, workforce agility, and AI adoption jointly relate to logistics resilience.

1.2. Research Problem

Previous studies examining technological drivers of supply chain and logistics resilience have primarily focused on AI-enabled analytics, blockchain, and Internet-of-Things-based visibility mechanisms (Kamble et al., 2020). However, relatively limited attention has been paid to how digitally enabled talent practices generate resilience outcomes through human-capital mechanisms. Although some studies have investigated workforce agility as an organizational outcome of digital human resource management (Muduli, 2016), few studies have directly connected workforce agility with logistics resilience as a downstream operational outcome or examined whether this human-capital pathway depends on firms' parallel investment in AI capabilities.

1.3. Literature Gap

The study identifies three research gaps.

Gap 1: Existing studies have mainly examined digital talent management as an antecedent of general human resource outcomes, such as employee engagement and turnover intention, while its influence on operational resilience outcomes in logistics contexts remains insufficiently explored

(Wright & McMahan, 1992).

Gap 2: Previous research on workforce agility has rarely been integrated with logistics resilience literature. Although these two constructs share strong conceptual connections, the mediating role of workforce agility between digital talent practices and resilience outcomes has not been empirically validated (Chowdhury & Quaddus, 2017).

Gap 3: Although artificial intelligence adoption has increasingly been examined as a driver of organizational resilience, its role as a boundary condition influencing the transmission mechanism from workforce agility to resilience remains unclear. Specifically, the moderating role of AI capability within this process has not been sufficiently examined (Wamba et al., 2021).

1.4 Research Objectives

Based on these research gaps, this study seeks to answer the following research questions:

RQ1: Does digital talent management positively affect logistics resilience?

RQ2: Does workforce agility mediate the effect of digital talent management on logistics resilience?

RQ3: Does AI adoption moderate the mediated path described above, and if so, at what stage in the causal chain does this moderation occur?

This study makes three contributions. Theoretically, it extends dynamic capabilities theory to the human-capital dimension of logistics resilience by examining workforce agility as a mediating mechanism. Methodologically, the study compares alternative locations of AI moderation and probes conditional indirect effects at low, mean, and high levels of AI adoption. The analysis locates the interaction within the proposed causal chain.

2. Literature Review

2.1. Concept Definition

Digital talent management refers to the use of digital platforms, data analytics, and automation technologies within organizations to identify, develop, recruit, and retain employees who contribute to organizational objectives (Collings & Mellahi, 2009). Workforce agility refers to employees' ability to respond quickly and flexibly to changes in work content and environmental conditions through adaptive behaviors, cognitive flexibility, and skill adjustment (Breu et al., 2002). AI adoption refers to the extent to which an organization applies artificial intelligence-based technologies, such as predictive analytics, machine learning, and automated decision-support systems, in logistics operations (Kamble et al., 2020). Logistics resilience refers to the capability of a logistics system to anticipate potential disruptions, absorb their impacts, and rapidly restore operational performance, as defined in the supply chain resilience literature (Ponomarov & Holcomb, 2009; Pettit et al., 2010).

2.2 Relationship between Digital Talent Management and Logistics Resilience

Research based on the resource-based view suggests that employees can become a source of sustained competitive advantage when their knowledge, skills, and capabilities are valuable, rare, and difficult to imitate (Barney, 1991). Building upon this perspective, digital talent management enables organizations to identify employee skill gaps, optimize workforce allocation, and implement timely training programs in response to changing operational requirements. Recent logistics and supply chain research also indicates that cross-system data can support more coordinated talent deployment across production, transport, and sales activities (Chen et al., 2024). Digital talent management can contribute to logistics resilience by strengthening data-driven workforce planning and deployment.

2.3 Mediating Mechanism: Workforce Agility

According to workforce agility theory, talent management practices are reflected in organizational outcomes through employee-level behaviors and cognitive capabilities (Crocitto & Youssef, 2003). Digital talent management tools, including real-time skill mapping, adaptive learning platforms, and

algorithm-based workforce deployment systems, enable employees to acquire new capabilities, adjust task assignments, shorten feedback cycles, and rapidly fill operational vacancies. These mechanisms collectively enhance workforce agility. Because logistics resilience depends heavily on the speed and flexibility with which frontline employees and managers can adjust operational activities during disruptions, workforce agility provides a theoretically meaningful mechanism connecting digital talent management with logistics resilience (Chowdhury & Quaddus, 2017).

2.4 The Moderating Effect of AI Adoption

At the same time, operations management research increasingly emphasizes the role of artificial intelligence in developing resilient supply chain and logistics systems. Applications such as demand forecasting, automated risk identification, and real-time resource allocation have become important mechanisms for improving operational responsiveness (Ivanov & Dolgui, 2020). From the perspective of organizational information processing theory, AI technologies enable organizations to transform operational data into timely and actionable responses, thereby strengthening the resilience benefits generated by an agile workforce (Dubey et al., 2022).

AI adoption is treated as a moderator of the relationship between workforce agility and logistics resilience. AI-enabled forecasting, risk identification, and resource-allocation systems provide operational information that can be used when employees and managers respond to disruptions. The interaction between AI adoption and workforce agility is estimated in the second-stage model.

3. Theoretical Framework and Hypothesis Development

Based on the resource-based view, dynamic capabilities theory and organizational information processing theory suggest that digital talent management provides support for human capital resources that affect logistics resilience through workforce agility; further, AI tools provide real-time operational information that can alter the relationship between workforce agility and logistics resilience. Fig 1 is the conceptual research framework of this paper.

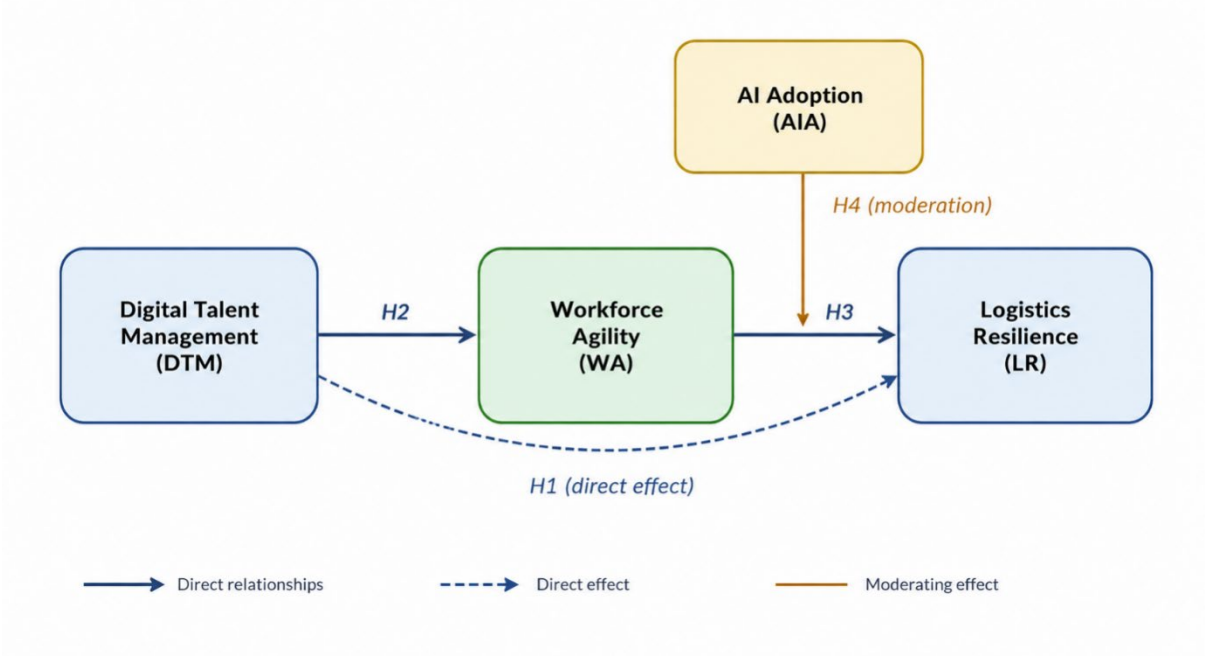


Fig.1: Conceptual Research Framework (Moderated Mediation)

H1: Digital talent management has a significant positive direct effect on logistics resilience.

H2: Digital talent management has a significant positive effect on workforce agility.

H3: Workforce agility mediates the relationship between digital talent management and logistics resilience.

H4: AI adoption moderates the mediated relationship between digital talent management and logistics resilience, such that the indirect effect through workforce agility is stronger at higher levels of AI adoption.

4. Methodology

4.1 Research Design

This study adopts a quantitative, cross-sectional survey design used to examine moderated mediation relationships among the study variables. The unit of analysis is the individual logistics or operations manager, selected as key informants given their direct visibility into both workforce practices and operational resilience outcomes within their organizations.

4.2 Data Source and Procedure

Data were collected through a structured questionnaire administered to logistics and operations managers across manufacturing, retail, and third-party logistics firms in mainland China. The survey was conducted between October and December 2023. A total of 600 questionnaires were distributed through alumni networks of three regional business schools and the official mailing lists of two provincial industry associations, including the Sichuan Logistics Association. After data screening, 382 valid responses were retained, representing an effective response rate of 63.7%. All respondents provided voluntary electronic informed consent. The study design, data security protocols, and consent procedures were formally reviewed and approved by the Institutional Review Board of Gingko College of Hospitality Management. Common method bias was addressed procedurally through respondent anonymity and randomized item ordering.

4.3 Variable Measurement

All constructs were measured using multi-item scales adapted from established prior literature and rated on five-point Likert scales. Table 1 summarizes the definitions and measurement sources for each variable.

Table 1. Variable Definitions and Measurements

Variable	Definition	Measurement Source
Digital Talent Management (DTM)	Use of digital platforms and analytics to attract, develop, deploy, and retain workforce capability.	Adapted from Tarique & Schuler (2010); Collings & Mellahi (2009)
Workforce Agility (WA)	Employees' capacity to adapt rapidly to changing tasks, roles, and operating conditions.	Adapted from Sherehiy & Karwowski (2014); Breu et al. (2002)
AI Adoption (AIA)	Extent of integration of AI-based analytics and decision-support tools into logistics operations.	Adapted from Belhadi et al. (2021); Kamble et al. (2020)
Logistics Resilience (LR)	Logistics system's capacity to anticipate, absorb, and recover from operational disruption.	Adapted from Ponomarov & Holcomb (2009); Pettit et al. (2010)
Control variables	Firm age, firm size, and high-technology certification status.	Standard controls following prior logistics resilience literature

4.4 Model Specification

The hypothesized moderated mediation model is specified as follows:

$$WAi = \alpha 0 + \alpha 1 \cdot DTMi + \alpha 2 \cdot Controlsi + \varepsilon 1i$$

$$LRi = \beta 0 + \beta 1 \cdot DTMi + \beta 2 \cdot WAi + \beta 3 \cdot AIAi + \beta 4 \cdot (WAi \times AIAi) + \beta 5 \cdot Controlsi + \varepsilon 2i$$

where LRi is the logistics resilience of firm i; DTMi is digital talent management; WAi is workforce agility (mediator); AIAi is AI adoption (moderator); WAi × AIAi is the mean-centered interaction term testing second-stage moderation; Controlsi is a vector of firm age, firm size, and high-technology certification; and ε1i, ε2i are error terms. Conditional indirect effects of DTM on LR through WA are

calculated at low (−1 SD), mean, and high (+1 SD) levels of AIA from the estimated DTM → WA coefficient and the corresponding simple slopes of WA → LR.

5. Results

5.1 Measurement Reliability and Validity

Internal consistency was assessed using Cronbach's alpha. The coefficients were 0.877 for digital talent management, 0.869 for workforce agility, 0.914 for AI adoption, and 0.908 for logistics resilience, all above the conventional 0.70 threshold. Harman's single-factor test showed that the first unrotated principal component accounted for 36.99% of the total variance across the 18 items, below the 50% majority-variance criterion (Podsakoff et al., 2003).

Table 2. Internal Consistency Reliability Summary (n = 382)

Construct	Cronbach's α
Digital Talent Management	0.877
Workforce Agility	0.869
AI Adoption	0.914
Logistics Resilience	0.908

5.2 Descriptive Statistics

Table 3 shows the descriptive statistics of the study's composite variables and control variables.

Table 3. Descriptive Statistics (n = 382)

Variable	Mean	Std. Dev.	Min	Max
Digital Talent Management	3.44	0.77	1.25	5.00
Workforce Agility	2.09	0.65	1.00	4.60
AI Adoption	3.08	0.90	1.00	5.00
Logistics Resilience	1.81	0.70	1.00	4.20
Firm Age (years)	21.00	10.62	2.00	39.00
Firm Size (category, 1–5)	3.01	1.41	1.00	5.00

5.3 Correlation Analysis

Table 4 presents the bivariate Pearson correlations. AI adoption is not significantly correlated with digital talent management ($r = .083$) or workforce agility ($r = .006$), while its correlation with logistics resilience is strong ($r = .680$, $p < .001$).

Table 4: Correlation Matrix (n = 382). *** p < 0.001, n.s. = not significant

Variable	1. DTM	2. WA	3. AIA	4. LR
1. Digital Talent Management	1.00	—	—	—
2. Workforce Agility	0.595***	1.00	—	—
3. AI Adoption	0.083 n.s.	0.006 n.s.	1.00	—
4. Logistics Resilience	0.266***	0.337***	0.680***	1.00

5.4 Regression and Mediation Results

Table 5 presents the hierarchical regression results. In the baseline model, digital talent management positively predicts logistics resilience ($\beta = 0.271$, $p < .001$, $R^2 = .093$). Digital talent management also predicts workforce agility ($\beta = 0.589$, $p < .001$, $R^2 = .361$). After workforce agility is added to the resilience equation, workforce agility remains significant ($\beta = 0.270$, $p < .001$), while the direct DTM coefficient declines to $\beta = 0.113$ ($p = .060$). The indirect workforce-agility pathway is examined further through the conditional indirect-effect estimates below.

Table 5. Hierarchical Regression Results (n = 382). Standardized coefficients. † p<0.10, *** p<0.001

Predictor	Model 1: WA	Model 2: LR (no mod.)	Model 3: LR (baseline)
Digital Talent Management	0.589***	0.113†	0.271***
Workforce Agility	—	0.270***	—
Firm age, size, high-tech (controls)	Included	Included	Included
R^2	0.361	0.139	0.093
Adjusted R^2	0.354	0.128	0.083
F-statistic	53.22***	12.16***	9.63***

5.5 Moderation and Moderated Mediation Analysis

Three candidate interaction locations were compared: DTM × AIA → WA, DTM × AIA → LR, and WA × AIA → LR. The front-stage interaction was not significant ($\beta = -0.046$, $p = .274$), while the back-stage interaction was significant ($\beta = 0.195$, $p < .001$). The main moderation specification places AI adoption on the WA → LR path; the corresponding interaction coefficient is reported below.

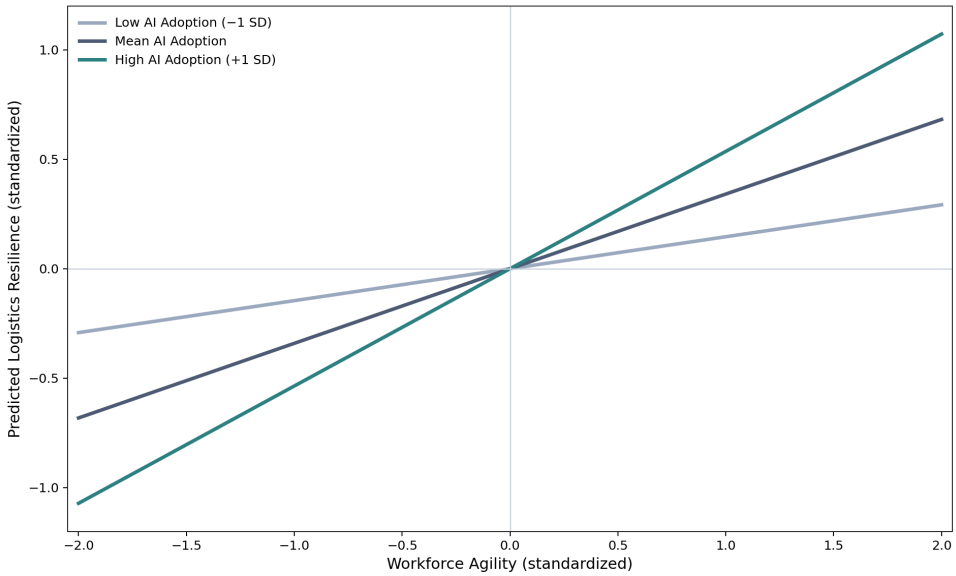


Fig.2: Moderating Effect of AI Adoption on the Workforce Agility-Logistics Resilience Path

Table 6 reports the simple slopes of workforce agility predicting logistics resilience at low, mean, and high levels of AI adoption. At the sample mean of AI adoption, the coefficient-product indirect effect is 0.201. The corresponding point estimates are 0.086 at low AI adoption and 0.316 at high AI adoption. These values are coefficient-product point estimates derived from the reported DTM → WA coefficient and the simple slopes in Table 6.

Table 6. Simple Slope Tests: Workforce Agility → Logistics Resilience at Levels of AI Adoption

Level of AI Adoption	Simple Slope (β)	SE	t	p
Low (-1 SD)	0.146	0.068	2.147	.032
Mean	0.341	0.062	5.500	<.001
High (+1 SD)	0.536	0.072	7.444	<.001

Table 7. Comparison of Candidate Moderation Specifications

Predictors	Model A: Front-Stage	Model B: Direct-Effect	Model C: Back-Stage (Final)
Interaction Term	DTM × AIA → WA	DTM × AIA → LR	WA × AIA → LR
Interaction (β)	-0.046 (p = .274)	0.138 (p < .001)	0.195 (p < .001)
Model R^2	0.364	0.528	0.615
Note	Front-stage interaction not significant	Direct-effect interaction significant	Back-stage interaction significant

5.6 Moderation Specification Comparison

Table 7 compares the three candidate locations of AI moderation. The front-stage interaction was nonsignificant (β = −0.046, p = .274), whereas the back-stage interaction was significant (β = 0.195, p < .001). The focal specification places AI adoption on the WA → LR path, along with the simple-slope

results. The coefficient-product index of moderated mediation is 0.115 (= 0.589 × 0.195). Conditional indirect effects are reported as coefficient-product point estimates.

6. Discussion

The results indicate that a human capital path for logistics resilience has been studied empirically to a lesser extent than purely technological explanations. Digital talent management improves the flexibility of the workforce, and in turn, a large portion of this effect is transmitted to logistics resilience; according to resource-based and dynamic capabilities theories on how human capital creates operational advantages, this occurs through the conversion of human capital (Teece et al., 1997). At the same time, the finding that AI adoption has little bivariate association with digital talent management or workforce agility, yet strongly moderates the agility-to-resilience path and shows a strong bivariate association with logistics resilience ($r = .680$, $p < .001$), suggests that AI adoption is associated with differences in how effectively an agile workforce's adaptability is translated into observable resilience outcomes, rather than being a downstream result of talent practices. This pattern can be read through the knowledge-based view and dynamic capabilities theory, which connect organizational capabilities with the use of knowledge resources in operations (Grant, 1996).

The results add a human-capital mechanism to the literature on AI and logistics resilience. The simple-slope pattern indicates that the positive association between workforce agility and logistics resilience is stronger at higher levels of AI adoption. The conditional indirect-effect values are coefficient-product point estimates based on the regression results and simple slopes.

The direct effect of digital talent management on logistics resilience is marginal after workforce agility is included ($\beta = 0.113$, $p = .060$). Additional mechanisms, including managerial decision quality, knowledge integration, and strategic resource deployment, may account for part of this residual pathway. Future research can examine these mechanisms using multidimensional measures of managerial and frontline agility.

AI adoption showed no substantial bivariate association with digital talent management or workforce agility, while its association with logistics resilience was strong. One interpretation is organizational separation between technology and talent decisions: AI adoption may be led primarily by operations or IT functions, whereas talent digitalization is managed through HR processes, budgets, and vendor arrangements. Under this configuration, AI can support demand forecasting and risk detection while workforce agility determines how effectively AI-derived information is translated into operational responses. This interpretation follows the significant back-stage interaction identified in the regression results.

7. Conclusion

7.1 Main Findings

Based on survey data from 382 logistics and operations managers, digital talent management positively predicts workforce agility, and workforce agility is positively associated with logistics resilience. AI adoption significantly moderates the workforce agility–logistics resilience relationship ($\beta = 0.195$, $p < .001$), with conditional indirect-effect point estimates increasing from 0.086 at low AI adoption to 0.316 at high AI adoption. The direct DTM coefficient becomes marginal after workforce agility is included ($\beta = 0.113$, $p = .060$).

7.2 Theoretical Implications

The study contributes to dynamic capabilities theory by empirically locating workforce agility as the operative mechanism linking digital talent management to logistics resilience. It also complements the knowledge-based view by demonstrating that organizational knowledge and talent resources create resilience primarily through the development of adaptive workforce capabilities, and by demonstrating that AI adoption functions as a boundary condition on the behavioral consequences of agility rather

than as an antecedent of agility itself — a distinction that prior single-mechanism studies of either talent management or AI adoption could not reveal in isolation.

7.3 Practical Implications

For logistics managers, the findings imply that digital talent management investments are most valuable when paired with parallel AI adoption. Digital transformation requires coordinated development of digital talent, HR analytics, and AI capability. An agile workforce supported by AI-enabled decision tools is more able to translate adaptability into resilient logistics operations. Accordingly, baseline AI infrastructure and digital talent management can be developed in parallel, reflecting their complementary roles in logistics resilience.

7.4 Limitations and Future Research

Several limitations define the scope of the findings. First, the cross-sectional design limits causal inference regarding the direction of the relationships tested; longitudinal designs can provide stronger evidence on temporal ordering. Second, the study relies on single-informant survey data; future research can strengthen the evidence through multi-informant designs. Third, the marginal direct effect of digital talent management after workforce agility is included ($\beta = 0.113$, $p = .060$) leaves room for additional mediating mechanisms, such as managerial decision quality or cross-functional coordination. Finally, future studies can test whether the moderating role of AI adoption generalizes across industries with different levels of technological maturity and regulatory contexts.

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