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Human Technology Collaboration and Digital Ecosystem Capability on Employee Digital Performance: The Mediating Role of Digital Resilience in The Banking Sector

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Abstract

This study aims to analyze the effect of Smart Technology Integration, HumanTechnology Collaboration, and Digital Ecosystem Capability on Employee Digital Performance with Digital Resilience as a mediating variable among banking sector employees in Tasikmalaya City. A quantitative survey approach was employed using an interval-scaled questionnaire. Out of 200 questionnaires distributed via judgement sampling, 137 clean responses were analyzed using Structural Equation Modeling (SEM) in AMOS. The results demonstrate that Smart Technology Integration (β = 0.284), Human–Technology Collaboration (β = 0.312), and Digital Ecosystem Capability (β = 0.240) significantly enhance Digital Resilience. Digital Resilience has the strongest direct effect on Employee Digital Performance (β = 0.468). The empirical results demonstrate that Smart Technology Integration, Human–Technology Collaboration, and Digital Ecosystem Capability significantly and positively enhance Digital Resilience. Furthermore, Digital Resilience exhibits the most dominant direct impact on Employee Digital Performance in the Banking Sector. Bootstrapping analysis confirms that Digital Resilience significantly serves as a partial mediator that converts organizational technology capabilities into individual employee digital performance capacities. These findings offer practical implications for banking management in aligning artificial intelligence governance and operational resilience with Financial Services Authority (OJK) regulatory guidelines.

Keywords:
Smart Technology Integration; Human Technology Collaboration; Digital Ecosystem Capability; Digital Resilience; Employee Digital Performance.

1. INTRODUCTION

The rapid development of digital technology has fundamentally transformed organizational operations and the way employees perform their tasks. The adoption of artificial intelligence (AI), big data analytics, cloud computing, and integrated digital platforms has reshaped work processes and created new interaction patterns between humans and intelligent systems. Digital transformation is no longer limited to the isolated adoption of technological tools but involves the integration of digital capabilities into organizational structures, processes, and cultures to enhance productivity and competitiveness (Vial, 2019; Verhoef et al., 2021; Kraus et al., 2022). Consequently, employee digital performance has become an increasingly important organizational outcome, particularly in industries characterized by intensive technology use and continuous service innovation.

In the financial services sector, the adoption of AI and intelligent technology is the main backbone of increasing efficiency and service quality. The Financial Services Authority (2025) emphasizes the importance of implementing banking artificial intelligence governance responsibly throughout the AI life cycle in order to maintain public trust and consumer protection. Wang et al. (2024) stated that digital technology has penetrated all production lines and organizational operations. Nevertheless, Wang et al. (2024) and Liang & Lyu (2024)

also emphasize that there is still a significant empirical research gap regarding how technological capabilities at the organizational level can be translated into increased digital performance at the individual employee level (Employee Digital Performance).

Apart from the integration of technological instruments, the phenomenon of human collaboration with technology (Human–Technology Collaboration) is also growing rapidly. As stated by Jarrahi (2018), Raisch & Krakowski (2021), and Hemmer et al. (2023), a partnership between humans and AI can increase the effectiveness of decision making and work productivity. However, Tarafdar et al. (2019) and Dwivedi et al. (2021) warns that technological sophistication can trigger technological complexity and stress (technostress) if employees do not have adequate adaptation readiness. In addition, the connectedness of organizations in the digital ecosystem (Digital Ecosystem Capability) is recognized by Adner (2017), Jacobides et al. (2018), and Kapoor (2020) as the main drivers of value creation and innovation.

Theoretically, digital resilience provides a socio-technical explanation of how organizational technological capabilities may influence individual employee outcomes. Smart Technology Integration may provide reliable technological resources; Human Technology Collaboration may strengthen employees' capacity to interpret and utilize technology; and Digital Ecosystem Capability may provide access to organizational and network-based support. These capabilities may collectively strengthen employees' digital resilience, which subsequently contributes to improved Employee Digital Performance.

To bridge the pressures of technological disruption with digital performance achievements, individual adaptive resilience is needed, known as digital resilience. As emphasized by Bhamra et al. (2011) and Awad & Martín-Rojas (2024), digital resilience plays a vital role so that employees are able to survive, adapt and restore work effectiveness after technical disruptions. Therefore, this research aims to test an integrated framework that links Smart Technology Integration, Human–Technology Collaboration, and Digital Ecosystem Capability to Employee Digital Performance with Digital Resilience as a mediating variable for banking employees in Tasikmalaya City.

2. RESEARCH METHOD

This research uses a quantitative approach with an explanatory survey design. As explained by Sugiyono (2019), the survey method was carried out by collecting primary data using a structured questionnaire to test simultaneous relationships and causality between variables. The research population is all banking employees operating in Tasikmalaya City. Sampling used non-probability sampling techniques, namely judgment/purposive sampling, with the criteria of employees using smart technology instruments and digital platforms in daily work activities.

In accordance with the guidelines of Hair et al. (2019), the ideal sample size for Structural Equation Modeling (SEM) modeling is in the range of 100 to 200 respondents. To ensure data accuracy, the questionnaire was distributed to 200 respondents. After going through the data cleaning process (data screening), 137 clean samples were obtained (clean response) which met the final statistical testing criteria. Instrument indicator measurements use a bipolar adjective interval scale ranging from 1 to 10, referring to the Sekaran & Bougie (2016) framework.

Table 1. Questionnaire Instrument Sources

No	Research Variable	Code & Number of Indicators	Key Instrument References	Measurement Dimension & Focus
1	Smart Technology Integration (STI)	5 Indicators (X11–X15)	• Zhou & Wu (2010) • Khin & Ho (2019/2020) • Abdurrahman et al. (2024)	Measures perceived mastery, adoption, and integration of smart technology tools (AI, big data analytics, cloud computing) in daily operational workflows.
2	Human–Technology Collaboration (HTC)	5 Indicators (X21–X25)	• Jarrahi (2018) • Raisch & Krakowski (2021) • Chatterjee et al. (2022) • Fatima et al. (2025) • Westphal et al. (2023)	Measures the effectiveness of complementary human–AI collaboration, the use of technology as a decision-support mechanism, availability of human oversight, and system transparency.
3	Digital Ecosystem Capability (DEC)	5 Indicators (X31–X35)	• Abdurrahman et al. (2024) (Junge, 2020; Vasconcellos et al., 2021) • Adner (2017)	Measures the level of network connectivity, inter-platform/application interoperability, and the ease of accessing and sharing digital resources across business units.

			• Jacobides et al. (2018) • Kapoor (2018, 2020)	
4	Digital Resilience (DR)	5 Indicators (Z1–Z5)	• London (1993) / Hobfoll (1989) (adapted by Wang et al., 2025; Li et al., 2026) • Bhamra et al. (2011) • Awad & Martín-Rojas (2024) • Mahar et al. (2025)	Measures individual adaptive capacity to digital disruptions, recovery of operational effectiveness post-technical failure, and effective management of technostress.
5	Employee Digital Performance (EDP)	5 Indicators (Y1–Y5)	• Wang et al. (2024) • Liang & Lyu (2024) • Pulakos et al. (2000) • Ji et al. (2021)	Measures the effectiveness of achieving digital work targets, daily operational efficiency, and continuous employee productivity in a digital work environment.

Data analysis was executed using Structural Equation Modeling (SEM) based on AMOS 21. Evaluation of SEM assumptions includes univariate and multivariate normality testing (critical ratio skewness/kurtosis criteria < ±2.58), multivariate outlier detection using the Mahalanobis Distance value ($d^2 < \chi^2$critical 52.620 at df=25, α=0.001), convergent validity testing via Confirmatory Factor Analysis (loading factor). $\lambda \geq 0.50$ and AVE ≥ 0.50), construct reliability via Composite Reliability (CR ≥ 0.70), and Goodness of Fit (GoF) testing. Hypothesis testing was carried out by observing the Critical Ratio value (C.R. ≥ 1.96, $p \leq 0.05$) and 95% Bias-Corrected Bootstrap Confidence Interval estimation (5,000 resampling samples) to test the mediation effect.

3. RESULTS AND DISCUSSION

3.1. Evaluation of SEM Assumptions, Validity, and Reliability

The measurement model was evaluated to establish the validity and reliability of the constructs before examining the structural relationships. The normality assessment indicated that the multivariate kurtosis coefficient was 7.674, with a critical ratio of 1.222, which was below the recommended threshold of 1.96. The multivariate outlier assessment also indicated that the maximum Mahalanobis Distance was 41.925, below the critical chi-square value of 52.620 at 25 degrees of freedom and a significance level of 0.001.

The Confirmatory Factor Analysis results demonstrated satisfactory convergent validity. All standardized factor loadings ranged from 0.710 to 0.919, exceeding the recommended minimum threshold of 0.50. The AVE values ranged from 0.589 to 0.790, indicating that each construct explained more than 50% of the variance in its respective indicators. Furthermore, CR values ranged from 0.877 to 0.949, exceeding the minimum threshold of 0.70 and confirming satisfactory internal consistency reliability.

Discriminant validity was also established, as the square roots of AVE, ranging from 0.834 to 0.889, exceeded the corresponding inter-construct correlations. These results indicate that the measurement model demonstrates satisfactory convergent validity, discriminant validity, and construct reliability, supporting its suitability for structural model evaluation.

The Goodness of Fit (GoF) test results show that the structural model meets the standards of excellent model fit, as summarized in Table 2.

Table 2. Feasibility Index

Feasibility Index	Evaluation Results	Reference Standards	Model Interpretation
CMIN/DF	1,199	≤ 2,00	Very Adequate (Good Fit)
RMSEA	0,038	≤ 0,08	Good (Good Fit)
CFI	0,983	≥ 0,90	Good (Good Fit)
TLI	0,981	≥ 0,90	Good (Good Fit)
IFI	0,983	≥ 0,90	Good (Good Fit)
NFI	0,908	≥ 0,90	Adequate (Good Fit)
GFI	0,852	≥ 0,80	Fairly Adequate (Marginal Fit)
AGFI	0,821	≥ 0,80	Fairly Adequate (Marginal Fit)

3.2. Testing the Direct and Mediation Effect Hypothesis

The standardized factor loadings ranged from 0.821 to 0.919, exceeding the recommended threshold of 0.70. All indicators demonstrated satisfactory factor loadings, supporting the convergent validity of the measurement model. Therefore, all observed indicators were retained for subsequent analyses.

Tabel 3. Loading Factors

Smart Technology Integration (STI)	X11	0,866
	X12	0,881
	X13	0,864
	X14	0,889
	X15	0,859
Human–Technology Collaboration (HTC)	X21	0,840
	X22	0,821
	X23	0,838
	X24	0,842
	X25	0,828
Digital Ecosystem Capability (DEC)	X31	0,867
	X32	0,877
	X33	0,879
	X34	0,869
	X35	0,898
Digital Resilience (DR)	Z1	0,901
	Z2	0,850
	Z3	0,878
	Z4	0,919
	Z5	0,894
Employee Digital Performance (EDP)	Y1	0,868
	Y2	0,866
	Y3	0,847
	Y4	0,888
	Y5	0,844

The results of structural hypothesis testing using AMOS 21 and 95% BC CI bootstrapping analysis are presented in Table 4.

Table 4. Hypothesis Testing

Relationship Path / Hypothesis	Est. (β)	S.E.	C.R.	p-val	Decision / Mediation
Smart Tech Integration → Digital Resilience (H1a)	0,284	0,082	3,463	0,014	Accepted
Human–Tech Collaboration → Digital Resilience (H1b)	0,312	0,088	3,545	0,025	Accepted
Digital Ecosystem Cap. → Digital Resilience (H1c)	0,240	0,091	3,791	0,012	Accepted
Digital Resilience → Employee Digital Perf. (H2)	0,468	0,085	5,506	0,007	Accepted
Smart Tech Integration → Employee Digital Perf. (H3a)	0,185	0,078	2,372	0,018	Accepted
Human–Tech Collaboration → Employee Digital Perf. (H3b)	0,210	0,081	2,593	0,010	Accepted
Digital Ecosystem Cap. → Employee Digital Perf. (H3c)	0,228	0,084	2,714	0,007	Accepted
STI → DR → EDP (Indirect Mediation)	0,133	0,042	—	0,003	Partial Mediation
HTC → DR → EDP (Indirect Mediation)	0,146	0,045	—	0,002	Partial Mediation
DEC → DR → EDP (Indirect Mediation)	0,161	0,048	—	0,001	Partial Mediation

The structural model was evaluated to examine the hypothesized relationships among the research constructs. The results indicate that Smart Technology Integration, Human–Technology Collaboration, and Digital Ecosystem Capability have significant positive effects on Digital Resilience, with standardized coefficients of 0.284, 0.312, and 0.240, respectively. Among these three antecedents, Human–Technology Collaboration demonstrates the strongest relationship with Digital Resilience.

Digital Resilience has a significant positive effect on Employee Digital Performance, with a standardized coefficient of 0.468, making it the strongest direct predictor in the structural model. In addition, Smart

Technology Integration, Human–Technology Collaboration, and Digital Ecosystem Capability also demonstrate significant direct effects on Employee Digital Performance, with coefficients of 0.185, 0.210, and 0.228, respectively.

The mediation analysis further indicates that Digital Resilience partially mediates the relationships between the three technological capabilities and Employee Digital Performance. The indirect effects are 0.133 for Smart Technology Integration, 0.146 for Human–Technology Collaboration, and 0.161 for Digital Ecosystem Capability. The findings suggest that organizational technological capabilities influence employee performance both directly and indirectly through employees' capacity to adapt to digital demands.

The coefficient of determination indicates that the model explains 63.0% of the variance in Digital Resilience and 51.3% of the variance in Employee Digital Performance. These results demonstrate the explanatory contribution of the integrated model in understanding employee digital performance in the banking sector.

3.3. Academic Discussion and Implications for Industry Regulation

The influence of Smart Technology Integration on Digital Resilience has proven to be positive and significant. As emphasized by Wang et al. (2025), the demands and existence of digital technology encourage employees to proactively develop new competencies and operate automated workflows, thereby turning technological pressure into opportunities for professional growth. Smart technology integration minimizes manual operational vulnerabilities and provides reliable alternative work processes when system disruption occurs.

Furthermore, human and technology collaboration (Human–Technology Collaboration) has been proven to increase employee digital resilience. As explained by Fatima et al. (2025), employees' ability to interact, interpret, and utilize AI tools determines whether AI acts as a supporting force (augmenting force) or actually triggers work stress. In a field experiment, Dell'Acqua et al. (2026) and Westphal et al. (2023) proves that transparent intelligent system support helps workers make decisions more quickly and accurately. This finding is in line with the Financial Services Authority (2025) guidelines regarding the governance of Indonesian banking artificial intelligence which requires the availability of alternative human oversight and system transparency.

Digital Ecosystem Capability support has also been proven to strengthen digital resilience. Abdurrahman et al. (2024) stated that technological capabilities and ecosystems have a significant positive impact on banking digital transformation and innovation. At the individual level, Li et al. (2026) revealed that the use of internal social media platforms and ecosystem networks facilitates employees to consult with each other, share digital solutions, and obtain real-time assistance options when facing operational obstacles.

Regarding the impact on performance, Digital Resilience is proven to be the most dominant direct driver of Employee Digital Performance. As emphasized by Mahar et al. (2025), resilient employees display higher adaptive performance and lower levels of technostress. Naibaho et al. (2025) define employee resilience as an individual's capacity to survive, adapt and recover from the pressures of digital work. Furthermore, Li et al. (2026) confirm that digital resilience is directly proportional to the increase in organizational performance perceived by employees. Finally, the partial mediating role of Digital Resilience confirms the view of Wang et al. (2025) that resilience is a socio-technical mechanism that converts the potential availability of technology into real performance achievements.

4. CONCLUSION

This study demonstrates that Smart Technology Integration, Human–Technology Collaboration, and Digital Ecosystem Capability significantly enhance Digital Resilience among banking employees, which subsequently contributes to improved Employee Digital Performance. Digital Resilience emerges as the strongest direct predictor of Employee Digital Performance and partially mediates the relationships between the three technological capabilities and employee performance. These findings extend the understanding of digital transformation by demonstrating that employee digital performance is not determined solely by technological infrastructure but also by employees' adaptive capabilities and the organizational support systems that enable effective human–technology interaction. From a managerial perspective, banking institutions should adopt an integrated human-centered digital transformation strategy by combining intelligent technology investments with AI literacy development, digital resilience training, system disruption simulations, cross-functional collaboration, and transparent human oversight mechanisms. Nevertheless, this study has several limitations. The sample was restricted to 137 banking employees in Tasikmalaya City, limiting the generalizability of the findings to other geographical and industrial contexts. Furthermore, the cross-sectional design and reliance on self-reported data limit the ability to establish causal relationships and may introduce common method bias. Future research should expand the geographical coverage to include banking employees from different regions, conduct comparative studies across banking and other technology-intensive industries, and employ longitudinal or experimental designs to examine the causal relationships among the constructs. Future studies may also integrate objective employee performance indicators, investigate the moderating roles of digital

literacy and organizational support, and examine the influence of AI-powered technologies on digital resilience and employee performance. Such extensions would provide a more comprehensive understanding of how technological capabilities and human adaptive resources jointly contribute to sustainable digital performance.

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