Journal of Office Administration: Education and Practice

Volume 6 Issue 1, pp.25-42 (2026)

Hompage: https://ejournal.unesa.ac.id/index.php/joa

Unveiling The Role of IT Capability in Human Resource Performance through Organizational Learning and Smart Working

Mar'atus Sholikah[ab], Heru Sulistyo[a]

[a]Master of Management Department, Faculty of Economics and Business, Universitas Islam Sultan Agung Semarang, Indonesia
[b]Department of International Business Administration, Politeknik Balekambang Jepara, Indonesia

ARTICLE INFO

Keywords:

IT Capability, organizational learning, smart working, HR performance

Article History:

Received April 1, 2026
Revised April 12, 2026
Accepted April 20, 2026
Available online May 1, 2026

Correspondence:

Mar'atus Sholikah, Master of Management Department, Faculty of Economics and Business, Universitas Islam Sultan Agung Semarang, Indonesia. Email: maratussholikah.polibang@gmail.com

ABSTRACT:

This study aims to examine the strategic role of IT capability in improving human resource performance through organizational learning and smart working. In the context of digital transformation, organizations must not only adopt technology but also learn how to utilize information technology to support flexible and adaptive work patterns. This study investigates how IT capability functions as a strategic capability that promotes smart working and strengthens organizational learning to enhance performance. This quantitative approach research administered a survey to 139 employees of the Roudlotul Mubtadi'in Educational Foundation, which was implementing an electronic work system. The findings indicate that IT capability significantly influences human resource performance both directly and indirectly through smart working. The results confirm that smart working serves as an important operational mechanism that integrates technological capability with performance outcomes. Although organizational learning does not directly affect performance, it helps establish the foundation for flexible organizational capabilities, which in turn can enhance adaptability and responsiveness to changing market conditions. Overall, the findings suggest that IT capability functions as a strategic factor in enhancing human resource performance in the digital era, particularly when organizations combine it with smart working and organizational learning.

INTRODUCTION

Digital transformation reshapes business processes, value creation, and human resource performance. For example, the emergence of workforce information systems, work automation tools, digital collaboration platforms, cloud computing, data analytics, and data-driven decision-making has changed how individuals manage work and make decisions more rapidly (Shiferaw & Birbirsa, 2025). Consequently, organizations now regard information technology transformation not merely as an administrative tool but as a strategic capability that helps them remain competitive in an increasingly competitive environment.

Mikalef et al. (2020) state that information technology (IT) capability reflects how effectively an organization generates strategic value by integrating IT management capability with digital infrastructure. Similarly, Ravichandran (2018) finds that combining IT capability with organizational strategy produces sustained competitive advantage. In line with Barney (1991), valuable, rare, inimitable, and non-substitutable resources can generate enduring advantages. IT capability fulfills these characteristics because it enables organizations to develop adaptive and knowledge-based work systems, which can lead to improved decision-making, enhanced efficiency, and better responsiveness to market changes.

However, possessing digital resources does not automatically improve performance. Organizations must develop the capability to leverage their technological resources to conduct productive internal processes, such as implementing effective training programs and fostering a culture of innovation among employees. Mollah et al. (2024) determine that digital capability significantly influences performance only when organizations support it with adequate digital leadership and organizational readiness. This finding indicates that internal mechanisms connect IT capability with performance outcomes.

One crucial mechanism is organizational learning. Argote & Miron-Spektor (2011) define organizational learning as the process of creating, retaining, and transferring knowledge to improve group performance. Obeso et al. (2020) argue that organizational learning enhances institutional adaptive capacity through the continuous acquisition and utilization of knowledge. Empirical evidence shows that organizational learning strengthens resilience, innovation, and performance improvement (Bogale et al., 2025; García-Martínez et al., 2023; Karnsomdee & Nakmanee, 2025; Vargas-Hernández & Almanza Jiménez, 2017).

In the era of digitalization, IT capability accelerates knowledge acquisition and dissemination. Through organizational learning, Otioma (2023) demonstrates that IT capability strongly influences innovation performance, particularly by enabling organizations to adapt quickly to market changes and foster a culture of continuous improvement. Mikalef et al. (2023) demonstrate that data-driven learning improves organizational capability by improving digital skills. This integration shows that technology's strategic value is in the organization's ability to stimulate collective learning.

Despite the extensive literature on IT capability and organizational learning, few studies link these factors to work system changes, especially in the context of emerging trends like smart working that require rethinking traditional work practices, which can lead to improved productivity and employee satisfaction, such as the need for new collaboration tools and management approaches that support remote work environments. Scholars are studying smart working more. Carbonara et al. (2022) describe smart working as a technology-based work system that emphasizes flexibility, autonomy, and results orientation while relying on integrated digital platforms. Zapata et al. (2024) argue that strong technological support and a learning-oriented culture enable smart working to enhance employee engagement and productivity. Furthermore, technology-based work flexibility can improve individual performance, particularly in knowledge-intensive work (Felstead & Henseke, 2017), by allowing employees to tailor their work environments and schedules to better suit their personal productivity patterns and learning styles.

Several studies report diverse findings regarding IT capability, organizational learning, smart working, and performance. Some researchers establish a direct correlation between IT capability and individual or organizational performance (Shiferaw & Birbirsa, 2025; Wicaksono & Utami, 2023), yet they neglect to address the mediating influences of organizational learning and smart working. Second, smart working emerges from technology-enabled organizational learning processes rather than from simple flexible work policies. Third, value-based educational institutions like private foundations and Islamic boarding schools in developing countries rarely study these correlations. Most studies focus on Google, Amazon, and Toyota, developed-country private-sector companies.

Roudlotul Mubtadi'in Educational Foundation operates in a complex socio-religious environment in pesantren colleges. Due to unique governance systems, limited technological infrastructure, and pressures to maintain traditional values amid digital modernization, the institution struggles to implement new technologies and adapt to changing educational needs (Jaenullah et al., 2022), which hinders its ability to enhance educational outcomes and meet the demands of a modern learning environment. These conditions provide a relevant practical context for evaluating how IT capability facilitates organizational learning and reconfigures work systems for educators and administrative staff. Fourth, several studies show inconsistencies in measuring and integrating organizational learning and digital capability. Many studies measure organizational learning through training or knowledge management indicators, ignoring systemic processes like leadership commitment and organizational integration, which are vital to promoting continuous improvement and adaptability; thus, these studies fail to capture the full scope of how these elements interact with digital resources to enhance overall organizational effectiveness. Consequently, a theoretical gap remains regarding how digital resources can improve human resource performance through organizational learning and smart working.

From the perspective of dynamic capability theory, Teece (2018) emphasizes that organizations must develop sensing, seizing, and transformation capabilities to survive in rapidly changing environments. In this study, IT capability functions as a foundational resource, organizational learning acts as the sensing and seizing mechanism, and smart working represents a form of capability transformation that reconfigures work systems. Thus, integrating technology, collective learning, and evolving work patterns forms a dynamic process that enhances employee performance. This study integrates the Resource-Based View and Dynamic Capability Theory to explain how learning processes and the reconfiguration of work systems influence performance. The study also defines smart working as a competency resulting from organizational technology learning, not just a flexible work policy, emphasizing its role in workforce innovation and adaptability. This research contributes to strategic management and digital human resource management literature and provides practical insights for organizations seeking digital transformation strategies that prioritize human resource performance.

METHOD

Data Collection and Sampling

Roudlotul Mubtadi'in Balekambang Educational Foundation is an Islamic educational institution based on the pesantren system that is currently undergoing digital transformation in its learning, administrative, and management systems. This study examines how organizational learning, smart working, and IT capability relate to digital-based human resource performance.

All educators involved in the study (N = 214) work across five formal educational units: Islamic Elementary School or Madrasah Ibtidaiyah (MI), Islamic Junior High School or Madrasah Tsanawiyah (MTs), Islamic Senior high school or Madrasah Aliyah (MA), Vocational High School or Sekolah Menengah Kejuruan (SMK), and a polytechnic. Because the population is clearly defined, the study applies proportional sampling to maintain structural representation across educational units.

The researchers determined the minimum sample size (n = 139) using the Krejcie and Morgan table and verified it with the Slovin formula (e = 5%). This sample size exceeds the minimum threshold of ten times the model's largest structural path (Hair & Alamer, 2022), indicating that it can estimate a moderately complex model.

To reduce non-response bias, the researchers collected data over three months using a multimode approach that combined online and offline distribution. Data screening identified missing values, multivariate outliers, and inconsistent response patterns. The final estimation used 139 valid observations.

Measurement

The researchers adapted the research instruments to the context of pesantren-based education and modified them from previously validated scales. All items were measured using a seven-point Likert scale. Jerez-Gómez et al. (2005), Jyothibabu et al. (2010), dan Pai & Huang (2011) define organizational learning as culture, learning strategy, knowledge transfer and integration, and leadership for learning.

The researchers adapted the smart working construct from Carbonara et al. (2023) and Rapp et al. (2006), covering technological, organizational-managerial, people, and planning and organization skill aspects. Meanwhile, IT capability—based on Mao et al. (2016), Turulja & Bajgoric (2016), and Zahra et al. (2019)—includes IT infrastructure resources, IT human resources, IT correlation resources, and IT knowledge. The human resource performance instrument—based on Pradhan & Jena (2017), Shao et al. (2024), dan Zhang et al. (2024)—measures task performance, adaptive performance, contextual performance, and innovative performance.

To ensure conceptual clarity and relevance to the pesantren-based educational context, the researchers conducted a pilot study (n = 35). The pilot test produced validity values ranging from 0.533–0.880 for organizational learning, 0.393–0.862 for smart working, 0.669–0.931 for IT capability, and 0.380–0.940 for human resource performance. The reliability coefficients in the pilot test ranged from 0.811 to 0.847.

Data Analyses

This study uses variance-based structural equation modeling to assess latent construct causal correlations. This method works for exploratory–predictive models with non-normal data and structural complexity (Hair & Alamer, 2022). The analysis is two-stage. First, researchers check the measurement model for convergent and discriminant validity. Second, they evaluate the structural model to test path significance, explanatory power (R^2), effect size (f^2), and predictive relevance (Q^2).

RESULTS AND DISCUSSIONS

Respondent Profiles

Table 1 presents the respondents' demographic profile. Female respondents (51.08%) outnumber male respondents (48.92%). This sex type distribution shows Indonesia's female teaching majority.

Table 1. Respondent Demographic Information

Profile	Categories	Frequency	%
Sex types	Male	68	48.92
	Female	71	51.08
Age (years old)	22 – 35	69	49.64
	36 – 45	62	44.60
	46 – 55	5	3.60
	56 – 65	3	2.16
Unit	MI	12	8.63
	MTs	51	36.69
	MA	19	13.67
	SMK	38	27.34
	Polytechnic	19	13.67
Latest education	S1	112	80.58
	S2	27	19.42

The largest age group (49.64%) is 22–35, followed by 36–45 (44.60%), 46–55 (3.60%), and 56–65 (2.16%). Eighty percent of respondents have bachelor's degrees, and nineteen percent have masters or S2. This data shows that they are relatively well-educated.

Model Assessment

The evaluation of the measurement model provides the foundation for assessing construct quality. The structural model in this study consists of reflective–formative higher-order constructs.

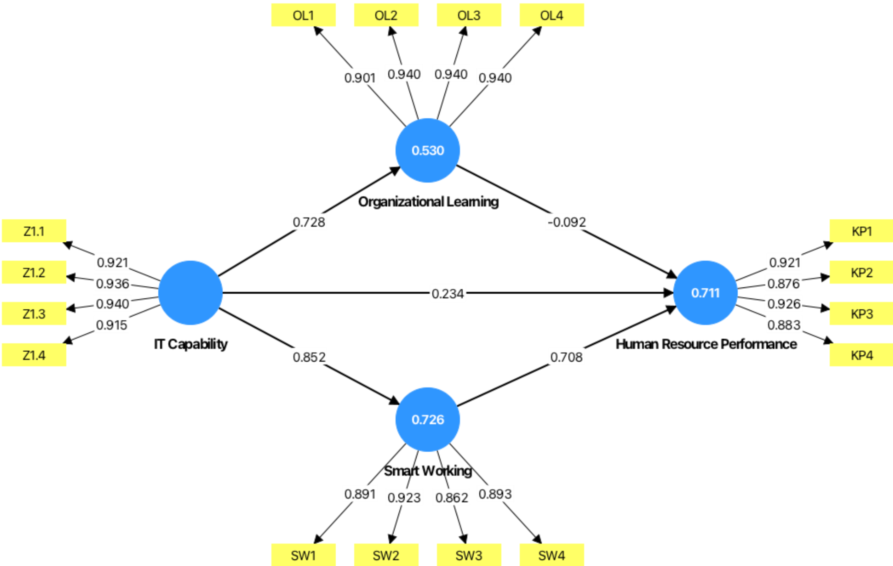


Figure 1. Outer Model

Lower-order components

The researchers evaluated factor loadings as the first step in assessing measurement quality criteria (see Table 2). All items exhibited factor loadings exceeding the minimum threshold of 0.70 (Hair & Alamer, 2022). The magnitude of the outer loadings confirms the reliability of the indicators.

Table 2. Outer Loadings

Variables	Indicators	*Loading factor*
HR Performance (Y)	KP1	0.921
	KP2	0.876
	KP3	0.926
	KP4	0.883
Organizational Learning (M1)	OL1	0.901
	OL2	0.940
	OL3	0.940
	OL4	0.940
Smart Working (M2)	SW1	0.891
	SW2	0.923
	SW3	0.862
	SW4	0.893
IT *Capability* (X)	Z1	0.921
	Z2	0.936
	Z3	0.940
	Z4	0.915

Next, the researchers assessed reliability using Cronbach's alpha, rho_a, and composite reliability. Table 3 shows Cronbach's alpha values from 0.915 to 0.948 and composite reliability values from 0.940 to 0.961. Both reliability indicators exceed the reliability statistics threshold of 0.70 (Wasko & Faraj, 2005). Higher rho_a values indicate higher reliability, with a research reliability threshold of 0.70 or higher (Henseler et al., 2016). All rho_a values exceed 0.70 (see Table 3). Therefore, the constructs demonstrate adequate reliability.

Table 3. Reliability and Validity Analysis

Construct	*a*	rho_a	rho_c	AVE
Y	0.923	0.927	0.946	0.813
X	0.946	0.949	0.961	0.861
M1	0.948	0.951	0.963	0.866
M2	0.915	0.917	0.940	0.797

Convergent and discriminant validity serve as statistical indicators of construct validity. Convergent validity is confirmed when the average variance extracted (AVE) reaches or exceeds the recommended threshold of 0.50 (Hair & Alamer, 2022). In this study, all AVE values exceed 0.50 (see Table 3), confirming convergent validity.

Table 4. Heterotrait-Monotrait Ratio (HTMT)

Construct	Y	X	M1	M2
Y				
X	0.820			
M1	0.686	0.762		
M2	0.903	0.913	0.858	

The researchers assessed discriminant validity using the heterotrait–monotrait ratio (HTMT), which estimates correlations among constructs. All HTMT values fall below the conservative threshold of 0.85, except for three values that remain below the more liberal threshold of 1.00 (see Table 4) (Henseler et al., 2015). In addition, the researchers applied the Fornell–Larcker criterion as a second method for evaluating discriminant validity Fornell & Larcker (1981). This method verifies that the square root of the AVE for each construct exceeds the inter-construct correlations represented by the diagonal elements, as shown in Table 5. Therefore, the results confirm discriminant validity.

Table 5. Fornell-Larcker Criteria

Construct	Y	X	M1	M2
Y	0.902			
X	0.770	0.928		
M1	0.643	0.728	0.930	
M2	0.834	0.852	0.798	0.893

Validating higher-order constructs

This study uses variance inflation factor (VIF) and outer weights to validate higher-order constructs. Table 6 shows that all VIF analysis values are below 5 for collinearity (Hair & Alamer, 2022).

Table 6. Variance Inflation Factor (VIF)

Construct	VIF
KP1	3.580
KP2	3.067
KP3	4.085
KP4	3.017
OL1	3.150
OL2	4.818
OL3	4.634
OL4	4.078
SW1	4.197
SW2	4.097
SW3	2.492
SW4	2.902
Z1.1	4.224
Z1.2	4.213
Z1.3	4.065
Z1.4	4.227

Next, all outer weights (see Table 7) are statistically significant (Hair & Alamer, 2022). When the p-value is below 0.05, researchers consider the indicator valid and retain it in the model (Sarstedt et al., 2019). Therefore, the results confirm a high level of construct validity that satisfies all specified criteria.

Tabel 7. Outer Weight

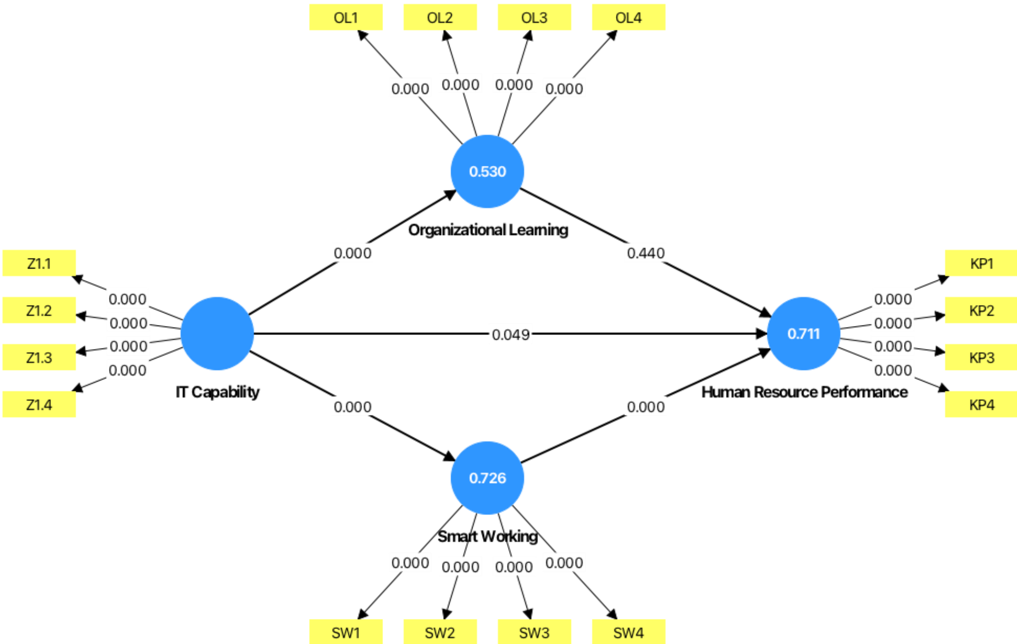
Construct	Outer Weight	T statistics	P values
Y1.1 → Y	0.302	30.967	0.000
Y1.2 → Y	0.255	27.958	0.000
Y1.3 → Y	0.279	27.496	0.000
Y1.4 → Y	0.272	29.577	0.000
M1.1 → M1	0.268	21.537	0.000
M1.2 → M1	0.281	20.535	0.000
M1.3 → M1	0.242	19.040	0.000
M1.4 → M1	0.285	23.970	0.000
M2.1 → M2	0.267	25.641	0.000
M2.2 → M2	0.280	32.030	0.000
M2.3 → M2	0.272	18.738	0.000
M2.4 → M2	0.301	23.534	0.000
X1.1 → X	0.268	26.014	0.000
X1.2 → X	0.257	46.596	0.000
X1.3 → X	0.293	29.309	0.000
X1.4 → X	0.259	34.533	0.000

Common Method Biases

Following Podsakoff et al. (2003), the study addresses common method bias (CMB) using the full collinearity VIF approach proposed by Kock et al. (2021). The internal model VIF values for all structural paths range from 2.492 to 4.818, which remain below the recommended threshold of 5.000 (Kock et al., 2021). Therefore, the model does not exhibit common method bias.

Structural Model Assessment

The study uses R^2 values for dependent variables to evaluate the strength of each structural path in the PLS-SEM model and to assess overall model quality. According to Villalva A. (2021), an R^2 value of 0.10 or higher indicates acceptable model fit. As shown in Table 8, all R^2 values exceed 0.10, indicating strong predictive capacity.



Gambar 2. Outer Model

Table 8. Assessment of Structural Model

Construct	Q^2 (>0)	R^2	SRMR (<0.10)
M1	0.518	0.530	0.089
M2	0.720	0.726	
Y	0.589	0.711	

The researchers further assess predictive relevance using the Stone–Geisser (Q^2) test. Q^2 values greater than zero indicate that the proposed structural model has significant predictive relevance for the endogenous constructs Hair & Alamer (2022). All Q^2 values exceed zero, demonstrating strong predictive relevance for the endogenous components. In addition, the standardized root mean square residual (SRMR) value is 0.089. Consistent with the criteria proposed by Hu & Bentler (1999), this SRMR value (SRMR < 0.10) confirms the model's acceptable fit.

Tabel 9. Total Direct Effect

Hypothesis			β	SD	T statistics	P values
H1	:	X → Y	0.234	0.119	1.969	0.049
H2	:	M1 → Y	-0.092	0.119	0.773	0.440
H3	:	M2 → Y	0.708	0.165	4.292	0.000

The results indicate that IT capability (X) significantly improves human resource performance (Y) (β = 0.234, p < 0.049), and smart working (M2) also significantly enhances human resource performance (Y) (β = 0.708, p < 0.000), as hypothesized in H1 and H3, respectively (see Table 9). Table 9 shows 95% confidence intervals from bootstrapping with 5,000 resamples. Non-zero confidence intervals indicate significant correlations.

Mediation Analysis

This study employs mediation analysis to explore the indirect correlations among X, M1, M2, and Y by examining whether organizational learning and smart working act as mediators (see Table 10). The analysis indicates that M2 significantly mediates the correlation between X and Y (H5: β = 0.109, p = 0.003). In contrast, M1 does not play a significant mediating role (H4: β = −0.067, p = 0.441) in the correlation between X and Y. Therefore, the study rejects H4 and accepts H5.

Tabel 10. Total Indirect Effect

Hypothesis			β	SD	T statistics	P values
H4	:	X → M1 → Y	-0.067	0.087	0.770	0.441
H5	:	X → M2 → Y	0.603	0.150	4.022	0.000

Discussion

This study examines how IT capability—an organization's ability to manage and use information technology—affects human resource performance directly and indirectly through organizational learning and smart working, mediating variables. IT capability positively and significantly impacts human resource performance, according to PLS-SEM. These findings suggest that managing, integrating, and using information technology improves human resource performance.

Consistent with the Resource-Based View (RBV) perspective (Barney, 1991), organizations can derive improved performance and competitive advantage from strategic capabilities and resources. In the digital environment, organizations view IT capability as a strategic capability that accelerates processes, speeds up decision-making, and improves the quality of work coordination. Mikalef et al. (2020) demonstrate that IT capability enhances organizational performance by optimizing data-driven processes. Similarly, Dubey et al.

(2020) show that digital capability improves organizational performance by integrating systems and increasing organizational responsiveness.

IT capability also affects smart working, particularly in how it allows organizations to adopt flexible work arrangements and improve remote team collaboration, which can lead to increased productivity and employee satisfaction. This suggests that an organization's IT readiness and maturity strongly affect flexible and technology-based work systems. According to the dynamic capability perspective proposed by Teece (2007), capability transformation involves an organization’s ability to convert resources into adaptive work systems. Through IT capability, institutions can develop digital work systems, online collaboration mechanisms, and task management platforms. Supporting this view, Chatterjee et al. (2023) and Cherbib et al. (2021) demonstrate that digital capability significantly influences digital work effectiveness and employee productivity.

Furthermore, Chuang et al. (2025) and Wang & Wang (2022) argue that technology-based work design can increase employee productivity by strengthening autonomy and self-regulation. These findings align with the present results because smart working represents a practical manifestation of IT capability utilization. The study also shows that smart working has a positive and significant effect on employee performance. This finding indicates that flexible, technology-based, and results-oriented work systems can enhance individual productivity and performance quality. When organizations provide adequate structural support, integrating technology into flexible work systems increases employee engagement and performance (Molino et al., 2020). Job flexibility also makes people happier at work and more productive (Allen et al., 2015).

The mediation analysis further shows that smart working significantly mediates the correlation between IT capability and human resource performance. This finding suggests that the influence of IT capability on performance intensifies when organizations deploy it via particular work systems. In other words, organizations must integrate technology into operational practices to maximize its impact on performance outcomes. This finding aligns with Khin & Ho (2019), who report that the impact of digital capability on performance becomes optimal when organizations combine it with operational capabilities.

Although IT capability significantly influences organizational learning, the results show that organizational learning does not significantly affect employee performance, indicating that while IT may improve learning processes, the outcome does not necessarily improve employee performance. Argyris & Schön (1997) say organizational learning boosts effectiveness.

Organizations learn to improve processes and capabilities and adapt to environmental changes, which can lead to enhanced competitiveness and innovation in response to market demands.

However, empirical research often shows that the effect of organizational learning on performance is indirect. Inthavong et al. (2023) and Chan et al. (2024) report that organizational learning influences firm performance through mediating mechanisms such as innovation. These findings indicate that when organizational learning affects performance, organizations must implement innovation or operational changes. Therefore, in this study, the organization may have partially embedded organizational learning into everyday work practices, which explains why it indirectly influences human resource performance.

Overall, the findings indicate that, in the context of digital transformation, the ability to utilize technology and digital work systems affects individual performance more directly than structural organizational learning mechanisms. IT capability functions as the strategic foundation, smart working serves as the operational mechanism, and human resource performance represents the primary outcome. Although organizational learning still contributes to strengthening organizational capacity, its impact on individual performance requires additional mechanisms to operate more effectively, such as enhanced communication channels and targeted training programs that align with digital transformation initiatives.

CONCLUSION

The study finds that information technology capability plays a crucial role in improving human resource performance. IT capability functions not merely as a supporting infrastructure but as a strategic asset that enables organizations to optimize smart working practices and develop work systems that are more adaptive, flexible, efficient, and responsive.

To translate IT capability into tangible performance improvements, smart working emerges as a critical mechanism. The integration of technology, work flexibility, and employee autonomy enhances productivity and improves the quality of outputs. These findings indicate that digital transformation strongly depends on the synergy between technological capability and flexible work design. Meanwhile, although organizational learning does not directly influence performance, it plays a strategic role in developing dynamic capabilities within organizations. Organizational learning helps organizations become more prepared to adapt and to strengthen IT capability in the long term, which is essential for maintaining competitiveness in a rapidly changing digital landscape.

The robustness test results indicate that the correlations among variables remain stable after the model includes control variables. In addition, the common method bias test confirms that the research model does not suffer from measurement method distortion. From a theoretical perspective, this study integrates the resource-based view and dynamic capability theory to explain human resource performance in the context of digital transformation. Consequently, these findings extend the existing literature. Organizations must prioritize IT capability, learning culture, and smart working practices to adapt to digital transformation and achieve sustainable and competitive human resource performance.

REFERENCES

Aguinis, H., Ramani, R. S., & Cascio, W. F. (2020). Methodological practices in international business research: An after-action review of challenges and solutions. *Journal of International Business Studies*, *51*(9). https://doi.org/10.1057/s41267-020-00353-7

Allen, T. D., Golden, T. D., & Shockley, K. M. (2015). How effective is telecommuting? Assessing the status of our scientific findings. *Psychological Science in the Public Interest*, *16*(2). https://doi.org/10.1177/1529100615593273

Argote, L., & Miron-Spektor, E. (2011). Organizational learning: From experience to knowledge. *Organization Science*, *22*(5). https://doi.org/10.1287/orsc.1100.0621

Argyris, Ch., & Schön, D. A. (1997). Organizational Learning: A Theory of Action Perspective. *Reis*, (77/78). https://doi.org/10.2307/40183951

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1). https://doi.org/10.1177/014920639101700108

Bernerth, J. B., & Aguinis, H. (2016). A Critical Review and Best-Practice Recommendations for Control Variable Usage. *Personnel Psychology*, *69*(1). https://doi.org/10.1111/peps.12103

Bogale, A. T., Birbirsa, Z. A., & Abegaz, M. B. (2025). The effect of organizational learning on firm performance: the mediating role of innovation capability in Ethiopian state-owned enterprises. *Discover Sustainability*, *6*(1). https://doi.org/10.1007/s43621-025-01277-8

Carbonara, N., Pellegrino, R., & Scozzi, B. (2022). The Impact of Smart Working on Organization Performance. *Electronic Journal of Knowledge Management*, *20*(3). https://doi.org/10.34190/ejkm.20.3.2611

Carbonara, N., Scozzi, B., & Pellegrino, R. (2023). Organizational readiness for smart working: a model and assessment tool. *Journal of Workplace Learning*, *35*(6). https://doi.org/10.1108/JWL-01-2023-0002

Chan, D. W. M., Sarvari, H., Golestanizadeh, M., & Saka, A. (2024). Evaluating the impact of organizational learning on organizational performance through organizational innovation as a mediating variable: evidence from Iranian construction companies. *International Journal of Construction Management*, *24*(9). https://doi.org/10.1080/15623599.2023.2239486

Chatterjee, S., Chaudhuri, R., Vrontis, D., & Kadić-Maglajlić, S. (2023). Adoption of AI integrated partner correlation management (AI-PRM) in B2B sales channels: Exploratory study. *Industrial Marketing Management*, *109*. https://doi.org/10.1016/j.indmarman.2022.12.014

Cherbib, J., Chebbi, H., Yahiaoui, D., Thrassou, A., & Sakka, G. (2021). Digital technologies and learning within asymmetric alliances: The role of collaborative context. *Journal of Business Research*, *125*. https://doi.org/10.1016/j.jbusres.2020.11.064

Chuang, Y. T., Chiang, H. L., & Lin, A. P. (2025). Insights from the Job Demands–Resources Model: AI's dual impact on employees' work and life well-being. *International Journal of Information Management*, *83*. https://doi.org/10.1016/j.ijinfomgt.2025.102887

Contreras, F., Baykal, E., & Abid, G. (2020). E-Leadership and Teleworking in Times of COVID-19 and Beyond: What We Know and Where Do We Go. In *Frontiers in Psychology* (Vol. 11). https://doi.org/10.3389/fpsyg.2020.590271

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics*, *226*. https://doi.org/10.1016/j.ijpe.2019.107599

Felstead, A., & Henseke, G. (2017). Assessing the growth of remote working and its consequences for effort, well-being and work-life balance. *New Technology, Work and Employment*, *32*(3). https://doi.org/10.1111/ntwe.12097

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

García-Martínez, I., Fernández-Batanero, J. M., Fernández-Cerero, J., & León, S. P. (2023). Analysing the Impact of Artificial Intelligence and Computational Sciences on Student Performance: Systematic Review and Meta-analysis. *Journal of New Approaches in Educational Research*, *12*(1). https://doi.org/10.7821/naer.2023.1.1240

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3). https://doi.org/10.1016/j.rmal.2022.100027

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management and Data Systems*, *116*(1), 2–20. https://doi.org/10.1108/IMDS-09-2015-0382

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*(July 2012), 1–55.

Inthavong, P., Rehman, K. U., Masood, K., Shaukat, Z., Hnydiuk-Stefan, A., & Ray, S. (2023). Impact of organizational learning on sustainable firm performance: Intervening effect of organizational networking and innovation. *Heliyon*, *9*(5). https://doi.org/10.1016/j.heliyon.2023.e16177

Jaenullah, J., Utama, F., & Setiawan, D. (2022). Resilience Model of the Traditional Islamic Boarding School Education System in Shaping the Morals of Student in the Midst of Modernizing Education. *Jurnal Kependidikan: Jurnal Hasil Penelitian Dan Kajian Kepustakaan Di Bidang Pendidikan, Pengajaran Dan Pembelajaran*, *8*(4). https://doi.org/10.33394/jk.v8i4.6013

Jerez-Gómez, P., Céspedes-Lorente, J., & Valle-Cabrera, R. (2005). Organizational learning capability: A proposal of measurement. *Journal of Business Research*, *58*(6). https://doi.org/10.1016/j.jbusres.2003.11.002

Jyothibabu, C., Farooq, A., & Pradhan, B. B. (2010). An integrated scale for measuring an organizational learning system. *Learning Organization*, *17*(4). https://doi.org/10.1108/09696471011043081

Karnsomdee, P., & Nakmanee, P. (2025). Innovative Leadership and Organizational Learning Affecting Adaptive Organizational Performance of Local Government Organization in Sakon Nakhon Province. *Review of Integrative Business and Economics Research*, *14*(2).

Khin, S., & Ho, T. C. F. (2019). Digital technology, digital capability and organizational performance: A mediating role of digital innovation. *International Journal of Innovation Science*, *11*(2). https://doi.org/10.1108/IJIS-08-2018-0083

Kniffin, K. M., Narayanan, J., Anseel, F., Antonakis, J., Ashford, S. P., Bakker, A. B., Bamberger, P., Bapuji, H., Bhave, D. P., Choi, V. K., Creary, S. J., Demerouti, E., Flynn, F. J., Gelfand, M. J., Greer, L. L., Johns, G., Kesebir, S., Klein, P. G., Lee, S. Y., … Vugt, M. van. (2021). COVID-19 and the workplace: Implications, issues, and insights for future research and action. *American Psychologist*, *76*(1). https://doi.org/10.1037/amp0000716

Kock, F., Berbekova, A., & Assaf, A. G. (2021). Understanding and managing the threat of common method bias: Detection, prevention and control. *Tourism Management*, *86*. https://doi.org/10.1016/j.tourman.2021.104330

Mao, H., Liu, S., Zhang, J., & Deng, Z. (2016). Information technology resource, knowledge management capability, and competitive advantage: The moderating role of resource commitment. *International Journal of Information Management*, *36*(6). https://doi.org/10.1016/j.ijinfomgt.2016.07.001

Mikalef, P., Islam, N., Parida, V., Singh, H., & Altwaijry, N. (2023). Artificial intelligence (AI) competencies for organizational performance: A B2B marketing capabilities perspective. *Journal of Business Research*, *164*. https://doi.org/10.1016/j.jbusres.2023.113998

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the correlation between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information and Management*, *57*(2). https://doi.org/10.1016/j.im.2019.05.004

Molino, M., Cortese, C. G., & Ghislieri, C. (2020). The promotion of technology acceptance and work engagement in industry 4.0: From personal resources to information and training. *International Journal of Environmental Research and Public Health*, *17*(7). https://doi.org/10.3390/ijerph17072438

Mollah, M. A., Ibrahim, Masud, A. Al, & Chowdhury, M. S. (2024). How does digital leadership boost competitive performance? The role of digital culture, affective commitment, and strategic agility. *Heliyon*, *10*(23). https://doi.org/10.1016/j.heliyon.2024.e40839

Obeso, M., Hernández-Linares, R., López-Fernández, M. C., & Serrano-Bedia, A. M. (2020). Knowledge management processes and organizational performance: the mediating role of organizational learning. *Journal of Knowledge Management*, *24*(8). https://doi.org/10.1108/JKM-10-2019-0553

Otioma, C. (2023). IT Capability, Organisational Learning and Innovation Performance of Firms in Kenya. *Journal of the Knowledge Economy*, *14*(3). https://doi.org/10.1007/s13132-021-00886-8

Pai, F. Y., & Huang, K. I. (2011). Applying the Technology Acceptance Model to the introduction of healthcare information systems. *Technological Forecasting and Social Change*, *78*(4), 650–660. https://doi.org/10.1016/j.techfore.2010.11.007

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. In *Journal of Applied Psychology* (Vol. 88, Number 5). https://doi.org/10.1037/0021-9010.88.5.879

Pradhan, R. K., & Jena, L. K. (2017). Employee Performance at Workplace: Conceptual Model and Empirical Validation. *Business Perspectives and Research*, *5*(1). https://doi.org/10.1177/2278533716671630

Rapp, A., Ahearne, M., Mathieu, J., & Schillewaert, N. (2006). The impact of knowledge and empowerment on working smart and working hard: The moderating role of experience. *International Journal of Research in Marketing*, *23*(3). https://doi.org/10.1016/j.ijresmar.2006.02.003

Ravichandran, T. (2018). Exploring the correlations between IT competence, innovation capacity and organizational agility. *Journal of Strategic Information Systems*, *27*(1). https://doi.org/10.1016/j.jsis.2017.07.002

Sarstedt, M., Hair, J. F., Cheah, J. H., Becker, J. M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal*, *27*(3). https://doi.org/10.1016/j.ausmj.2019.05.003

Shao, Z., Li, X., Luo, Y., & Benitez, J. (2024). The differential impacts of top management support and transformational supervisory leadership on employees' digital performance. *European Journal of Information Systems*, *33*(3). https://doi.org/10.1080/0960085X.2022.2147456

Shiferaw, R. M., & Birbirsa, Z. A. (2025). Digital technology and human resource practices: A systematic literature review. *Heliyon*, *11*(2). https://doi.org/10.1016/j.heliyon.2025.e41946

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13). https://doi.org/10.1002/smj.640

Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning*, *51*(1). https://doi.org/10.1016/j.lrp.2017.06.007

Turulja, L., & Bajgoric, N. (2016). Innovation and Information Technology Capability as Antecedents of Firms' Success. *Interdisciplinary Description of Complex Systems*, *14*(2). https://doi.org/10.7906/indecs.14.2.4

Vargas-Hernández, J. G., & Almanza Jiménez, R. (2017). Organizational Learning and Resilience for Effective Organizational Development. *International Journal of Advanced Scientific Research & Development*, *04*(0101).

Villalva A., J. E. (2021). Structural equation models - PLS in engineering sciences: a brief guide for researchers through a case applied to the industry. *Athenea*, *2*(4). https://doi.org/10.47460/athenea.v2i4.17

Wang, Y. Y., & Wang, Y. S. (2022). Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior. *Interactive Learning Environments*, *30*(4). https://doi.org/10.1080/10494820.2019.1674887

Wasko, M. M. L., & Faraj, S. (2005). Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS Quarterly: Management Information Systems*, *29*(1). https://doi.org/10.2307/25148667

Wicaksono, H., & Utami, N. N. (2023). The Influence of Organizational Learning and it Capability on Employee Performance Using Knowledge Sharing as a Variable Intervening in the Pasuruan District DPRD Secretariat. *International Journal of Social Science and Human Research*, *6*(11). https://doi.org/10.47191/ijsshr/v6-i11-71

Zahra, M., Hameed, W. U., Fiaz, M., & Farhan Basheer, M. (2019). Information technology capability a tool to expedite higher organizational performance. *UCP Management Review*, *3*(1).

Zapata, L., Ibarra, G., & Blancher, P. H. (2024). Engaging new ways of work: the relevance of flexibility and digital tools in a post-COVID-19 era. *Journal of Organizational Effectiveness*, *11*(1). https://doi.org/10.1108/JOEPP-04-2022-0079

Zhang, X., Qi, Z., Ma, L., & Zhang, G. (2024). Assessing the Curvilinear Correlation in Employee Digital Performance: A Task-Technology Fit Perspective. *International Journal of Human-Computer Interaction*. https://doi.org/10.1080/10447318.2024.2327181