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The Role of Dynamic Capabilities in Accelerating Service Performance: Synergistic Effects of Robotic Process Automation and Logistics Competence at PT Pos Indonesia

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***Keywords**: Robotic Process Automation, Logistics Competencies, Dynamic Capabilities, Logistics Service Performance, SEM-PLS, Digital Transformation, State-Owned Enterprises*

Abstract

***Purpose**: This study examines the direct and indirect effects of Robotic Process Automation (RPA) and Logistics Competencies on Logistics Service Performance through Dynamic Capabilities at PT Pos Indonesia. **Methods**: An explanatory quantitative approach was employed using a cross-sectional survey of 172 managerial and supervisory employees. Data were collected using a 1–5 Likert-scale questionnaire and analysed using SEM-PLS with 1,000 bootstrap resamples. **Results**: The results support all seven hypotheses. RPA and Logistics Competencies significantly enhance Dynamic Capabilities ($\beta = 0.392$ and 0.384), while Dynamic Capabilities significantly improve Logistics Service Performance ($\beta = 0.354$). Significant indirect effects were also found for RPA ($\beta = 0.139$) and Logistics Competencies ($\beta = 0.136$) through Dynamic Capabilities. The model explains 46.8% of the variance in Dynamic Capabilities and 60.9% in Logistics Service Performance. **Implications**: The findings highlight that digital transformation requires more than technological investment. PT Pos Indonesia should integrate end-to-end RPA implementation with continuous development of logistics competencies and dynamic capabilities to achieve sustainable improvements in logistics service performance.*

INTRODUCTION

Global logistics industry is undergoing significant transformation driven by rapid digitalization, changing customer expectations, and increasing market uncertainty. To remain competitive, logistics firms must continuously adapt their operational capabilities and business models. Dynamic Capability Theory explains how organizations develop the ability to sense opportunities, seize them, and transform organizational resources to respond effectively to environmental changes (Teece, 2021). Consequently, dynamic capabilities have become an essential strategic foundation for logistics companies seeking sustainable competitive advantage in the digital era.

As the national postal operator, PT Pos Indonesia faces substantial challenges resulting from digital disruption. The continuous decline in conventional mail services has forced the company to accelerate its digital transformation while simultaneously improving the performance of its logistics business. Meanwhile, customers increasingly expect logistics services that are fast, transparent, reliable, and flexible (Verhoef et al., 2021). However, PT Pos Indonesia continues to experience operational challenges, including bureaucratic procedures, shipment tracking inaccuracies, and delivery delays, reducing its competitiveness against more agile private logistics providers.

One promising solution is the implementation of Robotic Process Automation (RPA), which automates repetitive administrative processes with high accuracy and efficiency. Previous studies have demonstrated that RPA significantly reduces processing time, minimizes human error, and improves operational efficiency across various industries (Wewerka & Reichert, 2022; Ivanov et al., 2023). In logistics operations, RPA can automate shipment documentation, manifest processing, data validation, and shipment status updates, thereby enhancing service efficiency. Nevertheless, technological implementation alone is insufficient without adequate organizational capabilities.

The effectiveness of digital transformation largely depends on logistics competence, which reflects an organization's ability to manage distribution networks, supply chain operations, and employee expertise efficiently (Chowdhury et al., 2022). Human capabilities remain essential for adapting technology to complex operational environments. Therefore, organizations require both technological capability and logistics competence to successfully improve logistics service performance.

Although previous studies have separately examined RPA adoption and logistics competence, limited research has investigated how these two capabilities jointly contribute to service performance within the Dynamic Capability framework. Existing research primarily focuses on operational efficiency or cost reduction resulting from digital technologies (Vial, 2021), while studies on RPA mainly emphasize the banking and public administration sectors rather than the logistics industry (Wewerka & Reichert, 2022). Furthermore, previous studies on logistics competence have reported inconsistent findings regarding its direct contribution to organizational performance and have rarely incorporated emerging digital technologies such as intelligent automation (Chowdhury et al., 2022; Christopher et al., 2023). This indicates a significant theoretical and empirical gap concerning the integration of technological capabilities and logistics competence in explaining logistics service performance.

To address this gap, this study proposes Dynamic Capability Theory as an integrative framework for explaining how Robotic Process Automation and logistics competence contribute to logistics service performance. Specifically, this research empirically examines the direct effects of RPA and logistics competence on logistics service performance, as well as the mediating role of Dynamic Capabilities in these relationships at PT Pos Indonesia.

The novelty of this study lies in developing an integrated model that positions Dynamic Capabilities as a mediating mechanism linking technological and human-based capabilities to logistics service performance. Unlike previous studies that predominantly examine RPA or logistics competence as separate determinants of organizational performance, this study conceptualizes RPA as a technological capability and logistics competence as an organizational and human capability that can be transformed into superior service performance through Dynamic Capabilities. This approach extends the Dynamic Capability perspective by explaining how the combination of algorithmic automation and human logistics competence can generate organizational adaptation and service improvement in a logistics enterprise. Furthermore, the study extends the application of Dynamic Capability Theory to the context of digital transformation in a state-owned logistics enterprise, a context that remains relatively underexplored in the existing literature.

The study contributes to the literature by extending Dynamic Capability Theory into the context of digital transformation in state-owned logistics enterprises and providing empirical evidence regarding the complementary roles of automation technology and organizational competence. The findings are expected to offer theoretical insights for strategic management and logistics research, while also providing practical implications for accelerating digital transformation and improving logistics service performance within the logistics industry.

MATERIAL

Dynamic Capability Theory

Dynamic Capability Theory explains an organization's ability to integrate, build, and reconfigure resources to respond to changing environments. Teece (2019, 2021) identifies three key processes: sensing opportunities, seizing opportunities, and transforming organizational resources. In logistics, dynamic capabilities help organizations adapt to technological disruption by combining digital technologies with organizational competencies (Helfat & Raubitschek, 2021). Thus, DCT provides the primary theoretical foundation for explaining how RPA and logistics competence improve service performance.

Resource-Based View (RBV)

The Resource-Based View argues that competitive advantage derives from valuable, rare, inimitable, and well-organized resources (Barney, 1991). In the digital context, these resources include technological capabilities and organizational knowledge (Barney et al., 2021). In this study, RPA represents a strategic technological resource, while logistics competence represents organizational knowledge, whose integration supports superior service performance.

Robotic Process Automation

RPA is software-based technology that automates repetitive, rule-based tasks with minimal human intervention (Syed et al., 2023). It can improve efficiency, reduce errors, and accelerate processes. In logistics, RPA supports activities such as document processing, shipment tracking, data synchronization, and system integration, thereby improving operational efficiency and service consistency.

Logistics Competence

Logistics competence refers to an organization's ability to effectively coordinate logistics resources, operational expertise, and supply chain activities. It includes technical skills and problem-solving capabilities that support efficient logistics operations and responses to disruptions and customer requirements (Ivanov et al., 2021). Therefore, logistics competence provides an important organizational foundation for digital transformation.

Digital Transformation Dynamic Capability

Digital Transformation Dynamic Capability refers to an organization's ability to continuously renew and reconfigure its capabilities in response to technological change (Schiavone et al., 2022). It involves sensing digital opportunities, seizing technological opportunities, and reconfiguring organizational resources, enabling organizations to translate digital investments into improved performance.

Service Performance

Service performance reflects an organization's ability to consistently deliver reliable, responsive, timely, and high-quality logistics services. It is influenced by effective operational processes and customer-oriented service delivery (Wamba et al., 2022). In this study, service performance represents the ultimate outcome of technological adoption and organizational capability development.

CONCEPTUAL FRAMEWORK

Effect of Robotic Process Automation on Dynamic Capabilities

The availability of advanced technological infrastructure, such as Robotic Process Automation (RPA) (X_1), can strengthen an organization's Dynamic Capabilities (Z). RPA provides integrated operational data that enables managers to identify opportunities and respond to changes more rapidly (Helfat & Raubitschek, 2021). The flexibility of software-based automation also allows organizations to adopt technological innovations without completely replacing existing information system architectures (Santos et al., 2023). Therefore, RPA can enhance organizational agility and facilitate the reconfiguration of internal resources.

H1: Robotic Process Automation (RPA) has a positive and significant effect on the Dynamic Capabilities of PT Pos Indonesia.

Effect of Logistics Competence on Dynamic Capabilities

Human resources with strong logistics competence provide an important foundation for developing organizational adaptability. Logistics Competence (X_2), including problem-solving skills and the ability to adapt to operational changes, enables employees to modify workflows and respond effectively to market disruptions (Teece, 2007). Competent employees also contribute to organizational learning and the continuous improvement of operational processes (Wong et al., 2025). Thus, higher logistics competence is expected to strengthen the Dynamic Capabilities of PT Pos Indonesia.

H2: Logistics Competence has a positive and significant effect on the Dynamic Capabilities of PT Pos Indonesia.

Effect of Dynamic Capabilities on Logistics Service Performance

Dynamic Capabilities (Z) enable organizations to sense changes, seize opportunities, and reconfigure resources in response to changing market conditions (Teece, 2007). In logistics operations, these capabilities allow organizations to adjust delivery capacity, warehouse resources, and operational processes according to fluctuations in demand. The ability to continuously reconfigure resources can improve operational efficiency and delivery reliability (Fugate et al., 2022). Therefore, stronger Dynamic Capabilities are expected to contribute to better Logistics Service Performance (Y).

H3: Dynamic Capabilities have a positive and significant effect on the Logistics Service Performance of PT Pos Indonesia.

Effect of Robotic Process Automation on Logistics Service Performance

Robotic Process Automation (RPA)(X_1) can directly improve Logistics Service Performance (Y) by reducing manual intervention in data processing, document verification, and other repetitive logistics activities. Automation can reduce processing time and minimize human errors, thereby improving operational consistency (Santos et al., 2023). In addition, digitalized workflows can enhance service speed and provide greater transparency in shipment tracking (Ivanov, 2024). Therefore, greater utilization of RPA is expected to improve logistics service performance.

H4: Robotic Process Automation (RPA) has a positive and significant effect on the Logistics Service Performance of PT Pos Indonesia.

Effect of Logistics Competence on Logistics Service Performance

Logistics Competence (X_2), including professional skills, digital literacy, and supply chain knowledge, is an important determinant of operational service performance. Competent logistics professionals are better able to manage distribution activities accurately and respond effectively to operational challenges (Christopher et al., 2022). Strong technical and operational competence can also support safer handling of shipments, improve order fulfillment, and ultimately enhance customer satisfaction (Wong et al., 2025). Thus, higher Logistics Competence is expected to improve Logistics Service Performance.

H5: Logistics Competence has a positive and significant effect on the Logistics Service Performance of PT Pos Indonesia.

Mediating Role of Dynamic Capabilities in the Relationship between Robotic Process Automation and Logistics Service Performance

Dynamic Capabilities (Z) may function as a mechanism through which RPA (X_1) contributes to Logistics Service Performance (Y). The adoption of automation technology does not automatically generate superior performance if organizations lack the ability to integrate the technology into new and adaptive operational routines (Ivanov, 2024). RPA therefore requires organizational capabilities that enable the integration, adaptation, and reconfiguration of resources and processes (Helfat & Raubitschek, 2021). Through this mechanism, Dynamic Capabilities can transform the technological benefits of RPA into improved operational flexibility and service performance.

H6: Dynamic Capabilities mediate the effect of Robotic Process Automation (RPA) on the Logistics Service Performance of PT Pos Indonesia.

Mediating Role of Dynamic Capabilities in the Relationship between Logistics Competence and Logistics Service Performance

Logistics Competence (X_2) can generate greater service performance when supported by organizational capabilities that enable knowledge and skills to be effectively mobilized and reconfigured. Individual expertise may not translate into superior performance when organizational structures limit innovation and operational adaptation (Christopher et al., 2022). Dynamic Capabilities facilitate the integration of employee knowledge and competencies into organizational processes and enable resources to be reallocated in response to operational requirements (Wong et al., 2025). Therefore, Dynamic Capabilities can serve as an important mechanism linking Logistics Competence to improved Logistics Service Performance.

H7: Dynamic Capabilities mediate the effect of Logistics Competence on the Logistics Service Performance of PT Pos Indonesia.

Based on the theoretical foundations and relationships discussed above, this study develops a conceptual framework to examine the relationships among Robotic Process Automation, Logistics Competence, Digital Transformation Dynamic Capability, and Logistics Service Performance. The proposed framework assumes that RPA and Logistics Competence influence Dynamic Capability, which subsequently contributes to Service Performance, while also considering their direct and indirect effects through the mediating role of Dynamic Capability. The conceptual framework is presented in Figure 1.

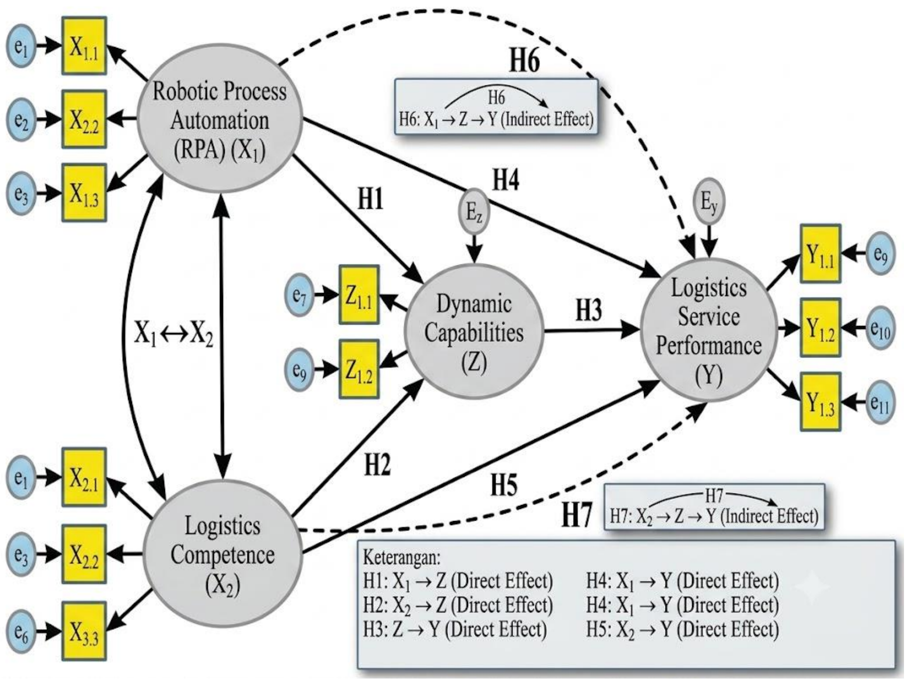

Figure 1. Conceptual Framework

METHODS

Research Design

This study employed a quantitative, descriptive-causal, cross-sectional research design to examine the relationships among Robotic Process Automation (RPA), Logistics Competence, Dynamic Capabilities, and Service Performance. Data were collected at a single point in time using a structured questionnaire. The unit of analysis was the individual, particularly managerial and supervisory personnel involved in logistics operations and digital transformation within PT Pos Indonesia.

Measurement

The study examined four latent constructs: Robotic Process Automation (X_1) and Logistics Competence (X_2) as independent variables, Dynamic Capabilities (Z) as a mediating variable, and Service Performance (Y) as the dependent variable.

RPA was measured through dimensions related to process efficiency, system integration, and operational scalability, adapted from Ivančić et al. (2021). Logistics Competence was assessed through transportation capability, warehousing capability, and personnel expertise, based on a modified measurement instrument from Chowdhury et al. (2023). Dynamic Capabilities were operationalized through the sensing, seizing, and transforming dimensions following Teece (2023). Service Performance was measured using dimensions of reliability, responsiveness, and digital service performance, adapted from Akter et al. (2022). All constructs were measured using reflective indicators.

Population and Sample

The target population consisted of managerial and supervisory personnel of PT Pos Indonesia, including managers and supervisors at the headquarters, Regional Offices, Main Branch Offices (KCU), and Branch Offices (KC). The organizational scope covered the headquarters, six regional offices, 42 KCU units, and 168 KC units, resulting in a target population of 300 individuals. The individual was selected as the unit of analysis because managerial perceptions and actions are directly related to the development of organizational dynamic capabilities.

The minimum sample size was determined using the Slovin formula with a 5% margin of error, resulting in a minimum requirement of 172 respondents. A purposive sampling technique was subsequently applied to select respondents with relevant knowledge of business process automation, supply chain management, and organizational digital transformation. Respondents were required to have at least two years of managerial experience and active involvement in the company's digital transformation initiatives.

Data Analysis

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The analysis consisted of two stages: evaluation of the measurement model (outer model) and evaluation of the structural model (inner model).

The measurement model was assessed through convergent validity, discriminant validity, and internal consistency reliability. Convergent validity was evaluated using outer loadings and Average Variance Extracted (AVE), with recommended thresholds of 0.70 and 0.50, respectively. Discriminant validity was assessed using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio. Reliability was evaluated using Cronbach's alpha and Composite Reliability, with values above 0.70 considered acceptable.

The structural model was subsequently evaluated using path coefficients, bootstrapping, coefficient of determination (R^2), predictive relevance (Q^2), and effect size (f^2). Hypotheses were tested using bootstrapping with a two-tailed significance level of 5%, where t-statistics ≥ 1.96 and p-values ≤ 0.05 indicated statistically significant relationships. R^2 was used to assess the explanatory power of the model, Q^2 to evaluate predictive relevance, and f^2 to determine the magnitude of individual effects.

RESULTS AND DISCUSSION

Demographic Characteristics

A total of 172 respondents participated in the study. Their demographic characteristics were assessed based on gender, age, education, work experience, and position. Overall, the respondents represented diverse backgrounds and were predominantly experienced managerial personnel in logistics operations.

Male respondents accounted for 108 (62.79%), while females accounted for 64 (37.21%). Most respondents were aged 31-35 years (24.42%), followed by 36-40 years (22.67%). Regarding education, 48.84% held a bachelor's degree (S1), followed by D3 (20.35%), D4 (15.70%), and master's degrees (15.11%).

In terms of work experience, the largest group had 11-15 years of experience (26.16%), followed by 6-10 years (22.09%) and 16-20 years (20.93%). Most respondents held managerial positions, particularly Executive Managers (51.00%), followed by Executive General Managers and Kurlog Operations Control Managers at KCU (14.00% each), and Kurlog Operations Control Managers at KC (16.00%). This profile indicates that the respondents generally possessed sufficient professional experience and organizational knowledge to assess RPA, logistics competence, dynamic capabilities, and logistics service performance.

Measurement (Outer) Model Evaluation

The measurement model was assessed in terms of convergent validity, discriminant validity, and reliability. Convergent validity was evaluated using outer loadings (>0.70) and AVE (>0.50), while discriminant validity was assessed using the Fornell–Larcker criterion and HTMT (<0.90). Reliability was evaluated using Cronbach's alpha and Composite Reliability (>0.70), following Hair et al. (2022). The result of outer loadins value, can be seen in table 1 below:

Table 1. Outer Loadings Value

Indicator	Variable	Outer Loading	T-Statistics	Desc.
RPA1	X_1 – Robotic Process Automation	0.737	20.924	Valid
RPA2	X_1 – Robotic Process Automation	0.778	19.976	Valid
RPA3	X_1 – Robotic Process Automation	0.753	19.411	Valid
RPA4	X_1 – Robotic Process Automation	0.770	23.032	Valid
RPA5	X_1 – Robotic Process Automation	0.866	38.438	Valid
RPA6	X_1 – Robotic Process Automation	0.836	27.021	Valid
KL1	X_2 – Logistics Competence	0.748	14.055	Valid
KL2	X_2 – Logistics Competence	0.703	18.319	Valid
KL3	X_2 – Logistics Competence	0.789	17.812	Valid
KL4	X_2 – Logistics Competence	0.736	12.807	Valid
KL5	X_2 – Logistics Competence	0.812	24.150	Valid
KL6	X_2 – Logistics Competence	0.813	25.442	Valid
KD1	Z – Dynamic Capabilities	0.779	23.046	Valid
KD2	Z – Dynamic Capabilities	0.791	22.922	Valid
KD3	Z – Dynamic Capabilities	0.784	22.496	Valid
KD4	Z – Dynamic Capabilities	0.760	19.868	Valid
KD5	Z – Dynamic Capabilities	0.820	27.768	Valid
KD6	Z – Dynamic Capabilities	0.761	22.592	Valid
KD7	Z – Dynamic Capabilities	0.746	20.340	Valid
KLAY1	Y – Service Performance	0.774	13.954	Valid
KLAY2	Y – Service Performance	0.766	13.878	Valid
KLAY3	Y – Service Performance	0.696	9.416	Valid
KLAY4	Y – Service Performance	0.737	13.389	Valid
KLAY5	Y – Service Performance	0.734	12.674	Valid
KLAY6	Y – Service Performance	0.812	22.912	Valid
KLAY7	Y – Service Performance	0.772	18.288	Valid
KLAY8	Y – Service Performance	0.788	18.509	Valid
KLAY9	Y – Service Performance	0.730	15.225	Valid

Source: Results of primary data analysis using the PLS algorithm and bootstrapping (n=172, resampling=1000), 2026

According to Hair et al. (2022), an indicator is considered to meet the criterion for convergent validity if it has an outer loading value greater than 0.700. Based on the test results, the highest loading value for variable X_1 was found in indicator RPA5 (Real-time synchronization of operational data) at 0.866, while for variable Y, indicator KLAY6 (Accessibility of the consumer service information portal) had the highest loading value at 0.812. All T-statistics values for the indicators were also well above 1.96, confirming that each indicator significantly represents its latent variable.

Average Variance Extracted (AVE)

The Average Variance Extracted (AVE) value in this study was used to measure the level of convergent validity of a construct by indicating the proportion of indicator variance that can be explained by the latent construct. The AVE test results are shown in table 2 below:

Table 2. AVE Values

Variablee	AVE	Desc.
Robotic Process Automation (X_1)	0.626	Valid
Logistics competence (X_2)	0.589	Valid
Dynamic Capabilities (Z)	0.605	Valid
Service Performance (Y)	0.573	Valid

Source: Analysis of primary data, 2026

According to Hair et al. (2022), a construct is said to have good convergent validity if its AVE value is greater than 0.500. All constructs in this study (table 2) have AVE values above 0.500 (ranging from 0.573 to 0.626), so it can be concluded that each latent variable is able to explain more than 50% of the variance in its indicators. Thus, the convergent validity of the measurement model is satisfied.

Fornell-Larcker Discriminant Validity

Fornell-Larcker discriminant validity testing ensures that each construct is distinct from other constructs. It is assessed by comparing the square root of AVE (√AVE) on the diagonal with the correlations between constructs. According to Hair et al. (2022), √AVE should be higher than all correlations in the same row and column. If this criterion is met, each construct demonstrates adequate discriminant validity and does not substantially overlap with other constructs. The result show in table 3 below:

Table 3. Fornell-Larcker Test Results

	X_1	X_2	Z	Y
X_1	0.791	0.555	0.605	0.669
X_2	0.555	0.768	0.601	0.627
Z	0.605	0.601	0.778	0.691
Y	0.669	0.627	0.691	0.757

Source: Analysis of primary data, 2026

Based on the Fornell-Larcker table, the square root of the AVE (diagonal) values for each construct - X_1 (0.791), X_2 (0.768), Z (0.778), and Y (0.757)—are greater than their correlation values with other constructs in the same row and column. This indicates that each construct possesses unique characteristics and that discriminant validity, as defined by the Fornell-Larcker criteria, is met. The implication of these results is that each construct has a clear identity and is capable of distinguishing itself from the other constructs. There is no indication that any variable measures the same concept as another variable (construct overlap), so the measurement model has good discriminant power.

Heterotrait-Monotrait Ratio (HTMT)

The Heterotrait-Monotrait Ratio (HTMT) is a method used to assess discriminant validity in PLS-SEM. Developed by Henseler et al. (2015), HTMT is considered more sensitive than the Fornell-Larcker criterion in detecting construct similarity. The purpose of HTMT is to ensure that each latent variable measures a distinct concept without excessive overlap with other constructs. HTMT is evaluated by comparing the correlations between indicators of different constructs with those of the same construct. According to Henseler et al. (2015), an HTMT value below 0.900 indicates adequate discriminant validity, while Hair et al. (2022) recommends a stricter threshold of 0.850. Therefore, HTMT values below the recommended threshold indicate that the constructs have adequate discriminant validity.

Table 4. HTMT Result

	X_1	X_2	Z	Y
X_1	-	0.614	0.668	0.705
X_2	0.614	-	0.638	0.637
Z	0.668	0.638	-	0.750
Y	0.705	0.637	0.750	-

Source: Analysis of primary data, 2026

Based on HTMT test results in the table 4 above, all HTMT values across constructs fall below the threshold of 0.900 (ranging from 0.614 to 0.750), thereby reinforcing the conclusion that discriminant validity among variables in this research model has been established.

Reliability Test

Reliability testing assesses the internal consistency of indicators in measuring a construct. In PLS-SEM, reliability is evaluated using Cronbach's Alpha (CA) and Composite Reliability (CR). A value of ≥ 0.70 indicates acceptable reliability. The reliability test results are presented in Table 5 below.

Table 5. Reliability Test Result

Variable	Cronbach's Alpha	Composite Reliability	Desc.
Robotic Process Automation (X_1)	0.880	0.909	Reliable
Logistics competence (X_2)	0.864	0.896	Reliable
Dynamic Capabilities (Z)	0.890	0.915	Reliable
Service Performance (Y)	0.907	0.924	Reliable

Source: Analysis of primary data, 2026

The Cronbach's Alpha values (0.864-0.907) and Composite Reliability values (0.896–0.924) in table 5, for all variables were above the 0.700 threshold. Thus, all research instruments are deemed reliable and consistent in measuring the intended constructs, meaning that the measurement model (outer model) as a whole meets the validity and reliability criteria to proceed to the structural model testing stage (inner model).

INNER MODEL ANALYSIS

Coefficient of Determination (R-square)

R-Square (R^2) indicates the ability of independent variables to explain the variation in the dependent variable. A higher R^2 value indicates that the model has greater explanatory power, while a lower value suggests that other factors outside the model contribute more to the dependent variable. The result shown in table 6 below:

Table 6. R-square Result

Variabel Endogen	R Square	R Square Adjusted	Category
Dynamic Capabilities (Z)	0.468	0.462	Moderat
Service Performance (Y)	0.609	0.602	Moderat-Strong

Source: Analysis of primary data, 2026

The R-Square value for Dynamic Capability (Z) is 0.468, indicating that 46.8% of its variance is explained by Robotic Process Automation (X_1) and Logistics Competence (X_2), while 53.2% is explained by other factors outside the model. Meanwhile, the R-Square value for Service Performance (Y) is 0.609, indicating that 60.9% of its variance is explained by Robotic Process Automation, Logistics Competence, and Dynamic Capability, while the remaining 39.1% is influenced by other factors. Based on Chin's criteria, an R^2 value of 0.468 is moderate, while 0.609 indicates relatively strong explanatory power.

Effect Size (f^2)

The effect size (f^2) was assessed to determine the magnitude of each exogenous construct's contribution to the endogenous construct. The f^2 analysis complements hypothesis testing by distinguishing statistically significant relationships from those with substantively meaningful effects. Following Hair et al. (2022), f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. The result of effect size shown in table 7 below.

Table 7. Effect Size Result

Variabel Eksogen	Variabel Endogen	F Square	Category
Robotic Process Automation (X_1)	Dynamic Capabilities (Z)	0.200	Medium
Logistics competence (X_2)	Dynamic Capabilities (Z)	0.192	Medium
Robotic Process Automation (X_1)	Service Performance (Y)	0.156	Medium
Logistics competence (X_2)	Service Performance (Y)	0.082	Small
Dynamic Capabilities (Z)	Service Performance (Y)	0.170	Medium

Source: Analysis of primary data, 2026

Based on Cohen's criteria (0.02 = small; 0.15 = moderate; 0.35 = large), the effects of Robotic Process Automation and Logistics Competence on Dynamic Capability are classified as moderate (0.200 and 0.192). The effect of Dynamic Capabilities on Service Performance is also classified as moderate (0.170), followed by the effect of Robotic Process Automation on Service Performance (0.156, moderate), while the effect of Logistics Competence on Service Performance is classified as small (0.082).

Predictive Relevance (Q Square)

Q^2 (Stone-Geisser's Q^2) evaluates the predictive relevance of a structural model in PLS-SEM. Unlike R^2, which measures explanatory power, Q^2 assesses how well the model predicts observed data for endogenous constructs. A Q^2 value greater than 0 indicates that the model has predictive relevance. The results shown in table 8 below:

Table 8. Q Square Result

Variabel Endogen	Q Square (Q^2)	Keterangan
Dynamic Capabilities (Z)	0.279	Good Predictive Relevance
Service Performance (Y)	0.336	Good Predictive Relevance

Source: Primary data analysis results, blindfolding procedure with omission distance D=7, 2026

The Q^2 values for Dynamic Capability (0.279) and Service Performance (0.336) are both greater than zero ($Q^2 > 0$), indicating that the structural model in this study has good predictive relevance for both of these endogenous variables.

HYPOTHESIS TESTING

The direct effect hypothesis was tested by examining the path coefficients (original sample), T-statistics, and P-values obtained from a bootstrapping procedure involving 1,000 resamples. The hypothesis was accepted if the T-statistics were ≥ 1.96 and the P-values were ≤ 0.05. The results of the SEM-PLS data analysis are illustrated in Figure 2 below:

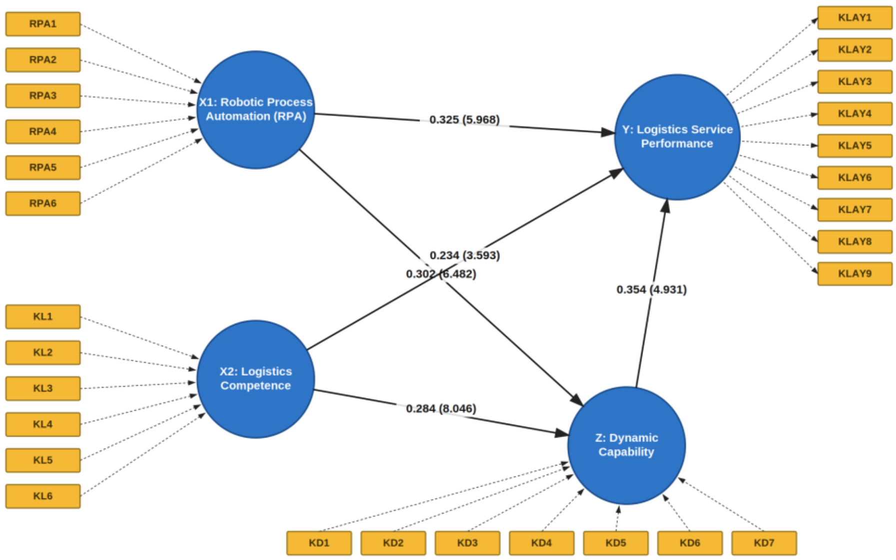

Figure 2. Bootstrapping Results (SEM-PLS Path Diagram)

Source: Results of primary data analysis using the PLS algorithm and bootstrapping (n=172, resampling=1,000), 2026

The hypotheses in this study are divided into two categories: direct and indirect effects, as described in Table 9 below:

Table 9. Hypotesis Analysis

Hypothesis	Path Relation	Path Coeff.	T-Statistics	P-Values	Desc.

Direct Effect					
H1	Robotic Process Automation (X_1) → Dynamic Capabilities (Z)	0.392	6.482	0.000	Significant (Accepted)
H2	Logistics competence (X_2) → Dynamic Capabilities (Z)	0.384	6.046	0.000	Significant (Accepted)
H3	Dynamic Capabilities (Z)→ Service Performance (Y)	0.354	4.931	0.000	Significant (Accepted)
H4	Robotic Process Automation (X_1)→ Service Performance (Y)	0.325	5.068	0.000	Significant (Accepted)
H5	Logistics competence (X_2) → Service Performance (Y)	0.234	3.593	0.000	Significant (Accepted)
Inderect Effect					
H6	$X_1 \rightarrow Z \rightarrow Y$	0.139	3.437	0.001	Significant (Accepted)
H7	$X_2 \rightarrow Z \rightarrow Y$	0.136	3.989	0.000	Significant (Accepted)

Source: Results of primary data analysis using bootstrapping with 1,000 resamples, 2026

Effect of Robotic Process Automation on Dynamic Capabilities (H1)

The results indicate that Robotic Process Automation (RPA) has a positive and significant effect on Dynamic Capabilities ($\beta = 0.392$, $t = 6.482$, $p < 0.001$). This finding suggests that greater adoption of RPA strengthens the organization's ability to adapt, innovate, and reconfigure its processes. RPA can reduce repetitive manual tasks and improve process accuracy, allowing organizational resources to be redirected toward higher-value activities and strategic adaptation. This finding is consistent with the dynamic capabilities perspective, which emphasizes that organizational capabilities enable firms to sense opportunities, seize them, and reconfigure resources in changing environments (Teece, 2007). The result also supports previous research highlighting the role of digital technologies in developing organizational agility and adaptive capabilities.

Effect of Logistics Competence on Dynamic Capabilities (H2)

Logistics Competence has a positive and significant effect on Dynamic Capabilities ($\beta = 0.384$, $t = 6.046$, $p < 0.001$). The finding indicates that employees' logistics knowledge, operational skills, and problem-solving capabilities contribute to the organization's ability to identify changes, respond to emerging opportunities, and reconfigure operational processes. From the dynamic capabilities perspective, organizational adaptation is grounded not only in technology but also in the skills, processes, and knowledge embedded within the organization (Teece, 2007). Thus, strengthening logistics competence provides an important human and operational foundation for digital transformation.

Effect of Dynamic Capabilities on Service Performance (H3)

Dynamic Capabilities have a positive and significant effect on Service Performance ($\beta = 0.354$, $t = 4.931$, $p < 0.001$), representing the strongest direct effect on Service Performance among the structural paths leading to the outcome variable. This result indicates that organizations with stronger capabilities to sense environmental changes, seize opportunities, and reconfigure resources are better positioned to improve service reliability, responsiveness, and operational performance. This finding is consistent with Teece (2007), who argues that dynamic capabilities provide the organizational foundation for sustained superior performance under rapidly changing conditions. The result therefore confirms that dynamic capabilities are not merely adaptive mechanisms but also important drivers of service outcomes.

Effect of Robotic Process Automation on Service Performance (H4)

RPA has a positive and significant direct effect on Service Performance ($\beta = 0.325$, $t = 5.068$, $p < 0.001$). This result demonstrates that automation contributes directly to improved logistics service performance by accelerating routine processes, reducing manual errors, and increasing process consistency. The finding indicates that the benefits of RPA extend beyond internal process efficiency to customer-facing service outcomes. However, the coefficient is lower than the effect of RPA on Dynamic Capabilities ($\beta = 0.392$), suggesting that part of the value generated by RPA may operate through organizational adaptation and transformation.

Effect of Logistics Competence on Service Performance (H5)

Logistics Competence has a positive and significant effect on Service Performance ($\beta = 0.234$, $t = 3.593$, $p < 0.001$), although its effect size is relatively small ($f^2 = 0.082$). The finding indicates that transportation knowledge, warehousing capabilities, and personnel expertise remain important determinants of logistics service performance. Nevertheless, the relatively small effect size suggests that logistics competence alone contributes less strongly to service performance than technological and dynamic capabilities. This result reinforces the argument that human expertise needs to be integrated with organizational transformation mechanisms to generate stronger performance outcomes.

Mediating Effect of Dynamic Capabilities on the Relationship between RPA and Service Performance (H6)

The indirect effect of RPA on Service Performance through Dynamic Capabilities is positive and significant ($\beta = 0.139$, $t = 3.437$, $p = 0.001$). This finding confirms that Dynamic Capabilities mediate the relationship between RPA and Service Performance. The significant direct effect of RPA on Service Performance ($\beta = 0.325$) together with the significant indirect effect indicates a complementary or partial mediation pattern, assuming the direct and indirect effects have the same positive direction. Thus, RPA improves service performance both directly through process automation and indirectly by strengthening the organization's ability to adapt and reconfigure its resources. This finding is consistent with the dynamic capabilities perspective, in which technological resources create greater value when organizations possess the capabilities required to integrate and reconfigure them (Teece, 2007).

Mediating Effect of Dynamic Capabilities on the Relationship between Logistics Competence and Service Performance (H7)

The indirect effect of Logistics Competence on Service Performance through Dynamic Capabilities is positive and significant ($\beta = 0.136$, $t = 3.989$, $p < 0.001$). This result demonstrates that Dynamic Capabilities provide an important mechanism through which logistics competence is translated into improved service performance. The finding suggests that employee knowledge and operational expertise generate greater value when they are incorporated into organizational processes for sensing changes, seizing opportunities, and reconfiguring resources. Consistent with Teece's (2007) framework, capabilities embedded in people and organizational processes can contribute to superior performance when they are effectively mobilized and transformed in response to environmental change. Given the significant direct effect of Logistics Competence on Service Performance ($\beta = 0.234$) and its significant indirect effect through Dynamic Capabilities, the mediation is also consistent with a partial mediation pattern, provided that the direct effect remains significant in the mediation model.

CONCLUSION AND RECOMMENDATION

Conclusion

This study concludes that Robotic Process Automation (RPA), logistics competency, and dynamic capabilities are important factors in improving logistics service performance at PT Pos Indonesia. RPA and logistics competency both have positive and significant effects on dynamic capabilities, while dynamic capabilities significantly enhance logistics service performance. RPA and logistics competency also have direct positive and significant effects on logistics service performance.

Furthermore, dynamic capabilities significantly mediate the relationship between RPA and logistics service performance as well as between logistics competency and logistics service performance. These findings indicate that the benefits of digital automation and employee competencies can be strengthened when the organization is able to effectively sense changes, adapt its resources, and transform its processes.

Overall, the findings demonstrate that successful digital transformation in the logistics sector does not depend solely on technological investment. It also requires strong organizational capabilities and competent human resources to integrate technology into business processes and continuously improve service performance.

RECOMMENDATION

Practical Recommendations.

PT Pos Indonesia is recommended to expand the implementation of RPA across logistics operations, including shipment processing, sorting, warehousing, transportation, and last-mile delivery. The company should also continuously develop employees' competencies in digital logistics, data analytics, artificial intelligence, supply chain management, and process automation. In addition, strengthening dynamic capabilities through organizational learning, cross-functional collaboration, innovation, and data-driven decision-making is essential to support sustainable digital transformation and service improvement.

Theoretical Recommendations.

This study contributes to Dynamic Capability Theory and the Resource-Based View by demonstrating that technology and human competencies can generate greater performance benefits when supported by organizational capabilities to integrate, adapt, and transform resources. Future theoretical development should therefore consider the interaction between digital technologies, human competencies, and organizational capabilities in explaining logistics service performance.

Recommendations for Future Research.

Future studies may incorporate additional variables such as digital leadership, organizational agility, innovation capability, supply chain integration, information technology capability, organizational learning, and digital organizational culture. Research may also examine other logistics companies and use longitudinal or mixed-method approaches to provide deeper insights into the long-term impact of digital transformation on logistics service performance.

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