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Factors Affecting the Efficiency of Reverse Logistics in E-commerce Warehouses in Nakhon Pathom Province

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Abstract
Background and Aim: In the context of E-commerce operations, Return Management plays a critical role in determining the overall efficiency of the sustainable supply chain. This study aims to: (1) examine the level of implementation of factors influencing the efficiency of Reverse Logistics in E-commerce warehouses in Nakhon Pathom Province, and (2) analyze the influence of such factors on Reverse Logistics Performance in these warehouses.
Materials and Methods: A quantitative research approach was employed. Data were collected through structured questionnaires from 100 warehouse personnel. The sample size was calculated using Green's (1991) method. Multiple Regression Analysis was used to assess the influence of independent variables, including the use of dummy variables to capture warehouse characteristics and management models.
Results: The findings revealed that all independent variables had a statistically significant influence on Reverse Logistics Performance at the 0.05 level. Key predictors included Process Clarity ($\beta = 0.421$, $p < .001$), Employee Capability ($\beta = 0.297$, $p < .001$), Technology Utilization ($\beta = 0.271$, $p = 0.002$), and Return Policy Clarity ($\beta = 0.241$, $p = 0.004$). Additionally, medium-sized (D1) and large-sized (D2) warehouses exhibited a positive influence, whereas 3PL management (D3) had a negative influence. The model explained 38.6% of the variance in Reverse Logistics Performance ($R^2 = 0.386$, Adjusted $R^2 = 0.360$)
Conclusion: The results suggest that enhancing technology utilization, strengthening employee capability, and improving process clarity are essential strategies for increasing the efficiency of return management. Furthermore, appropriate decisions regarding warehouse size and management models can significantly improve the long-term capacity and performance of the Reverse Logistics process in E-commerce environments.
Keywords: Return Management; Reverse Logistics Performance; E-commerce Warehouses; Return Policy

Introduction

In an era where E-commerce is experiencing rapid growth, logistics systems, particularly the management of returned products or Reverse Logistics, have become a critical strategy for maintaining customer satisfaction and gaining a competitive advantage (Sansaluna et al., 2024). Due to the high return rates in online transactions, business operators are compelled to develop warehouses that can effectively support the reverse logistics process in terms of time, accuracy, and cost. (Sarkar, Bhattacharya, & Sarkar, 2025)

The application of circular economy principles to warehouse logistics systems, including sustainable Reverse Logistics management, has been found to enhance operational efficiency while mitigating environmental impacts (Rashid, 2025). Simultaneously, Jiang et al. (2024) emphasized that the capability to manage logistics during peak order periods, particularly within Urban Warehouse Networks, is a significant factor influencing the efficiency of Reverse Logistics in the E-commerce sector. In the context of warehouses in Thailand, the study by Phunlarp et al (2025) revealed that implementing Warehouse Management Systems (WMS) alongside process improvements plays a vital role in elevating warehouse operational efficiency, which is inherently linked to the Reverse Logistics process. Notably, streamlining warehouse operations through a well-structured system can substantially reduce processing time, errors, and costs.

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Accordingly, the factors influencing the efficiency of Reverse Logistics in E-commerce warehouses are of critical importance, particularly in Nakhon Pathom Province, which has been identified in its provincial development plan as the "logistics hub of the Western Region." The province has experienced continuous growth in distribution and warehousing activities, especially in the districts of Mueang Nakhon Pathom, Sam Phran, and Phutthamonthon, which serve as key nodes in the country's main transport network (Nakhon Pathom Province, 2023). The development plan further highlights the enhancement of logistics potential through major projects such as road network development to support the E-commerce industry, the promotion of zones for private warehouses, and the improvement of logistics data systems. These initiatives underscore the province's growing role as a central warehouse and distribution hub for Thailand's central and western regions. This research, therefore, aims to analyze internal organizational factors, namely the use of technology, employee capability, process clarity, characteristics of the warehouse, and return policy, to propose strategic approaches for enhancing the efficiency of Reverse Logistics in alignment with the local context.

These factors align with the Resource-Based View and Process Management Theory, which emphasize internal capabilities and workflow clarity as drivers of logistics performance. However, limited research has explored how these factors affect reverse logistics in regional logistics hubs like Nakhon Pathom, creating a need for context-specific investigation.

Objectives

1. To study the level of implementation of the factors influencing the efficiency of Reverse Logistics in E-commerce warehouses in Nakhon Pathom Province.
2. To analyze the influence of the factors on the efficiency of Reverse Logistics in E-commerce warehouses in Nakhon Pathom Province.

Literature review

Concept of Reverse Logistics

Reverse Logistics is regarded as a key strategy in modern logistics operations, focusing on managing the movement of goods or materials from the point of consumption back to the point of origin. This is particularly relevant in businesses that primarily operate through digital channels, such as E-commerce, which experiences significantly higher return rates than traditional retail businesses. It is also crucial for businesses emphasizing sustainable development, which prioritize efficient resource utilization, waste reduction, and support for the circular economy.

Reverse Logistics encompasses more than merely accepting returned products. It includes processes such as quality inspection, refurbishment for reuse, disassembly for remanufacturing, material recycling, and even environmentally friendly waste disposal. These processes not only help reduce organizational costs but also enhance customer satisfaction, strengthen brand loyalty, and improve the organization's image regarding social and environmental responsibility (Amri, Lamsali, & Rajemi, 2025).

Effective Reverse Logistics management requires a deep understanding of internal organizational factors. Previous research has identified key components influencing the success of Reverse Logistics in warehouses, which include: Technology Utilization, Process Clarity, Employee Capability, Warehouse Characteristics, and Return Policy Clarity. These factors are interrelated and systemically influential. These five factors can be framed within key theories such as the Resource-Based View and Lean Logistics, which emphasize the role of internal capabilities and process standardization in achieving operational efficiency. Each can be elaborated as follows:

1. Technology Utilization

The integration of technology into Reverse Logistics management enhances operational speed, accuracy, and cost-effectiveness. Widely used systems include Warehouse Management Systems (WMS), Radio Frequency Identification (RFID), and automated inspection systems. These tools allow for real-time tracking and analysis of returned products. Furthermore, applying Industry 4.0 technologies such as the

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Internet of Things (IoT) and Big Data Analytics can further optimize processes (Jarašūnienė, Gureckienė, & Čižiūnienė, 2023; Issah, Agboyi, Hanson, & Adarkwa,2024; Phunlarp et al., 2025)

2. Process Clarity

Clarity in the steps involved in managing returned products—from receiving, inspecting, and deciding whether to reuse, restock, or resell is vital. A structured, standardized, and traceable process reduces discrepancies, work time, and errors, especially for businesses with high volumes of returned goods, such as E-commerce or recycling-based industries (Chaabane, Cherbonnier, Kober, Paquet, & Montecinos, 2024; Issah et al., 2024)

3. Employee Capability

While technology is vital, knowledgeable and skilled employees who can assess, inspect, and make decisions regarding returned items remain essential organizational assets. Continuous training and fostering understanding of Reverse Logistics processes are crucial. Research shows that analytical and decision-making skills among employees significantly affect sorting accuracy and error reduction in storage (Ramasamy & Anand, 2024; Issah et al., 2024; Mbago, 2025)

4. Warehouse Characteristics

Warehouse characteristics, including size, storage capacity, level of automation, and management model (in-house or third-party logistics providers - 3PL), influence Reverse Logistics efficiency. Larger warehouses equipped with smart technologies and integrated with production and information systems handle returns more effectively in terms of time, accuracy, and cost (Sarkar, Bhattacharya, & Sarkar, 2025)

5. Return Policy Clarity

A clear, easily understood, and accessible return policy is crucial for minimizing confusion, reducing disputes, and ensuring a smooth return process. Flexible policies enhance customer satisfaction and trust, while also enabling organizations to systematically forecast and plan reverse logistics operations (Amri et al., 2025; Issah et al., 2024)

Returns management is a fundamental component of Reverse Logistics systems and has a direct impact on the efficiency of warehouses in the E-commerce sector. Haddad and Bhat (2025) provided an in-depth view of the demographic and environmental factors affecting consumer return behavior, which reflects the impacts on warehouse systems through four key performance indicators:

1. Return Cycle Time

This indicator reflects the efficiency of the return process in terms of speed, from the time a customer initiates a return until the item arrives at the warehouse and is ready for subsequent steps such as inspection, sorting, or resale. Haddad and Bhat (2025) noted that return methods, such as home pick-up or drop-off at service points, affect this timeframe. Urban areas, with better infrastructure and transport networks, typically experience shorter cycle times compared to rural areas that depend more on third-party logistics and face accessibility challenges (Mourya, 2025; Richards, 2025)

2. Sorting Accuracy

This indicator concerns the warehouse's ability to accurately and swiftly identify and sort returned products. Although Haddad and Bhat (2025) did not focus specifically on sorting, the widespread “bracketing” behavior—ordering multiple sizes, colors, or models with the intent to return those not selected—has a direct impact. Returns in incomplete conditions, such as open boxes, missing tags, or damaged packaging, complicate decisions on whether to restock, resell, or dispose. Without robust technology or standardized procedures, sorting errors and delays are more likely (Mourya, 2025)

3. Average Return Cost

Return costs significantly impact business profitability. Richards (2025) reported that in 2024, the total return-related cost in the United States reached $890 billion, with E-commerce accounting for approximately 25% of that amount. These costs include transportation, inspection, sorting, and damage-related expenses. Without a strategic Reverse Logistics plan or cross-departmental coordination (e.g., customer service, warehousing, and transportation), the average cost per return can increase significantly (Richards, 2025)

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4. Customer Satisfaction

Customer satisfaction is a key indicator affecting brand loyalty and the likelihood of repeat purchases. Haddad and Bhat (2025) found that 68% of consumers value convenient return processes, such as label-free, box-free, and contactless returns. If warehouses fail to meet these expectations, customers may become dissatisfied and avoid future purchases from the platform. Therefore, customer satisfaction is directly related to a warehouse's ability to offer flexible and user-friendly return services (Mourya, 2025; Richards, 2025).

Together, these four KPIs provide a practical and interconnected measure of reverse logistics performance, covering both operational and customer-facing outcomes.

Table 1 summarizes the variables synthesized to construct the conceptual framework of this study.

Variable	Researchers (Year)
Independent Variables	
1. Technology Utilization	Issah et al. (2024); Phunlarp et al. (2025)
2. Employee Capability	Ramasamy & Anand (2024); Issah et al. (2024); Mbago (2025)
3. Process Clarity	Chaabane et al. (2024); Issah et al. (2024)
4. Warehouse Characteristics	Sarkar, Bhattacharya, & Sarkar (2025)
5. Return Policy Clarity	Amri et al. (2025); Issah et al. (2024)
Dependent Variables	
6. Return Cycle Time	Haddad & Bhat (2025); Mourya (2025); Richards (2025)
7. Sorting Accuracy	Haddad & Bhat (2025); Mourya (2025)
8. Average Return Cost	Haddad & Bhat (2025); Richards (2025)
9. Customer Satisfaction	Haddad & Bhat (2025); Mourya (2025); Richards (2025); Issah et al. (2024)

Conceptual Framework

This study categorizes the research variables into two main groups: Independent Variables and Dependent variables. The details are as follows:

1. Independent Variables

The independent variables refer to internal organizational factors that are expected to influence the efficiency of Reverse Logistics in E-commerce warehouses. There are five variables included:

1.1 Technology Utilization

This refers to the extent to which technologies such as Warehouse Management Systems (WMS), barcode scanning, or RFID systems are applied in the Reverse Logistics process. Indicators include the level of technology adoption in return management and the frequency of use. This variable is measured using a 5-point Likert scale.

1.2 Employee Capability

This refers to the knowledge, skills, and experience of personnel involved in managing returned goods. Indicators include years of relevant experience and frequency of training in Reverse Logistics. This variable is measured using a 5-point Likert scale.

1.3 Process Clarity

This refers to the degree of clarity, systemization, and traceability of the procedures involved in handling returned goods, such as sorting, quality inspection, and return dispatch. Indicators include the availability of written procedures/manuals and the existence of a quality control system. This variable is measured using a 5-point Likert scale.

1.4 Warehouse Characteristics

This refers to the structural attributes of the warehouse, including warehouse size (small, medium, large) and the management model (in-house or outsourced to third-party logistics providers – 3PL). This variable is collected on a **nominal scale** and will be included in the analysis as a dummy variable.

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1.5 Return Policy Clarity

This refers to the clarity, flexibility, and appropriateness of the organization's return policy, such as return timeframe, return conditions, and communication with customers. Indicators include the existence of a written and clearly defined return policy and the ease of understanding such policies. This variable is measured using a 5-point Likert scale.

2. Dependent Variable

Reverse Logistics Performance in E-commerce Warehouses

This refers to the outcome of the Reverse Logistics process that reflects efficiency in terms of time, accuracy, cost, and customer satisfaction. The key indicators include:

1. Return Cycle Time
2. Sorting Accuracy
3. Average Return Cost
4. Customer Satisfaction regarding the return process

This variable is measured using a 5-point Likert scale, and the average score of the four indicators is used to construct a composite index of overall performance.

Independent Variables

1. Technology Utilization
2. Employee Capability
3. Process Clarity
4. Warehouse Characteristics
5. Return Policy Clarity

Dependent Variable

Reverse Logistics Performance in E-commerce Warehouses

1. Return Cycle Time
2. Sorting Accuracy
3. Average Return Cost
4. Customer Satisfaction

Figure 1 Research Conceptual Framework

Methodology

1. Research Design

This study adopted a quantitative design to examine the influence of internal organizational factors (independent variables) on reverse logistics efficiency (dependent variables) in E-commerce warehouses. A 5-point Likert scale was used to collect structured, quantifiable data on implementation levels of the independent variables. Efficiency was assessed through four dependent variables: return cycle time, sorting accuracy, average return cost, and customer satisfaction. While qualitative methods provide valuable contextual understanding, a quantitative approach was deemed more suitable for analyzing statistical relationships across a broader sample.

2. Population and Sample

2.1 Population

The population consisted of personnel involved in Reverse Logistics operations in E-commerce warehouses located in Nakhon Pathom Province, including warehouse or logistics operations staff, warehouse or logistics supervisors, and warehouse or logistics managers.

2.2 Sample

The sampling procedure utilized both purposive sampling and stratified sampling, based on warehouse characteristics (size: small, medium, large; and management model: in-house or 3PL).
Purposive sampling was used to identify warehouses engaged in reverse logistics, followed by stratified sampling to ensure representation across size and management types. Respondents were proportionally selected from each stratum. The sample size was calculated using Green's (1991) formula:

$n \geq 50 + 8(m)$

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where *m* is the number of independent variables.

$n \geq 50 + 8(5)$

$n \geq 90$

Thus, the appropriate sample size for this analysis was determined to be 100 respondents.

3. Research Instrument

3.1 Questionnaire

The primary instrument for quantitative data collection was a closed-ended questionnaire, divided into three sections:

Section 1 General information of the respondents, including job position (e.g., operations staff, supervisor, manager), and work experience (years in logistics or Reverse Logistics-related work).

Section 2: Assessment of the level of implementation for the five independent variables, measured using a 5-point Likert scale. The five independent variables were (1) Technology Utilization, (2) Process Clarity, (3) Employee Capability, (4) Warehouse Characteristics, and (5) Return Policy Clarity.

Section 3 Assessment of Reverse Logistics Performance, comprising four key indicators, measured on a 5-point Likert scale. The four performance indicators included (1) Return Cycle Time, (2) Sorting Accuracy, (3) Average Return Cost, and (4) Customer Satisfaction.

3.2 Instrument Validation and Reliability

Content Validity: The questionnaire was reviewed by three experts to assess the appropriateness and alignment of the items with the research objectives. The Index of Item-Objective Congruence (IOC) was applied, with an acceptable threshold of ≥ 0.5 (Rovinelli & Hambleton, 1977). All items scored within a range of 0.67 to 1.00, indicating satisfactory content validity.

Reliability Testing: A pilot test was conducted with 30 participants with characteristics similar to the target sample. Cronbach's Alpha was used to assess internal consistency. According to Cronbach (1977), $\alpha \geq 0.84$ is considered high reliability. The overall alpha coefficient obtained was 0.78, which is considered acceptable for research purposes, particularly in exploratory or applied logistics research where values between 0.70 and 0.80 are commonly deemed sufficient. Item analysis was also conducted, and no substantial improvement in reliability was found by removing any item.

4. Data Collection

Quantitative data were collected from warehouse employees and managers in Nakhon Pathom Province through both direct distribution and online survey platforms. Data collection was conducted from April to June 2025. The online questionnaire was distributed via Google Forms, while printed versions were administered directly by the researcher. To ensure consistency across both modes, the same questionnaire, instructions, and measurement scales were used. Direct supervision during in-person distribution and response restrictions on the online platform helped maintain data quality and minimize response bias.

5. Data Analysis

Descriptive Statistics were used to summarize the characteristics of the sample and their responses regarding the implementation level of various factors. The analysis included:

Part 1 Basic respondent information (e.g., job position, logistics experience), presented using frequency and percentage.

Part 2: Levels of implementation of internal organizational factors and Reverse Logistics Performance, analyzed using mean and standard deviation (SD). A 5-point Likert scale was used, with interpretation adapted from Boonchom Sisaard (2017) as follows:

Mean Score	**Interpretation**
4.51 – 5.00	Highest
3.51 – 4.50	High
2.51 – 3.50	Moderate
1.51 – 2.50	Low
1.00 – 1.50	Lowest

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Inferential Statistics were employed to examine the influence of independent variables on Reverse Logistics Performance. Multiple Regression Analysis was used to test the hypotheses. The criteria for evaluating the model's appropriateness included:

1. R and R^2,
2. Adjusted R^2,
3. F-statistic for overall model significance, and
4. Statistical significance threshold at $p < 0.05$

To ensure model reliability, the study also examined multicollinearity by evaluating the Variance Inflation Factor (VIF) of each independent variable. A VIF less than 5 was considered acceptable (Hair et al., 2019)

In addition, the basic assumptions of regression analysis were tested, including:

1. Linearity
2. Independence of errors
3. Homoscedasticity
4. Normality of residuals to ensure the model was statistically sound and appropriate for explaining relationships between variables (Field, 2018; Hair et al., 2019)

6. Research Ethics

The study complied with ethical standards for human research. Informed consent was obtained from all participants. The research objectives were communicated, and personal data confidentiality was strictly maintained throughout the study.

Results

1. Level of Implementation of Factors Influencing the Efficiency of Reverse Logistics in E-commerce Warehouses in Nakhon Pathom Province

Table 2 General Information of Respondents

Item	Frequency (n)	Percentage (%)
Job Position		
- Operations Staff	63	63
- Warehouse Supervisor	24	24
- Warehouse Manager	13	13
Work Experience		
- Less than 1 year	7	7
- 1–3 years	32	32
- 4–6 years	35	35
- 7–10 years	18	18
- More than 10 years	8	8

According to Table 2, the general characteristics of the 100 respondents involved in Reverse Logistics in E-commerce warehouses in Nakhon Pathom Province reveal that the majority were operations staff, comprising 63 individuals or 63% of the sample. This was followed by warehouse supervisors (24 individuals, 24%) and warehouse managers (13 individuals, 13%)

In terms of work experience, the largest group had 4–6 years of experience, totaling 35 individuals (35%). The next largest group had 1–3 years (32 individuals, 32%), followed by 7–10 years (18 individuals, 18%). Respondents with more than 10 years of experience totaled 8 individuals (8%), while those with less than 1 year of experience accounted for only 7 individuals (7%)

Table 3 Analysis of Implementation Level of Internal Organizational Factors

Independent Variable	Mean	Standard Deviation (SD)	Implementation Level
Technology Utilization	4.61	0.23	Highest
Employee Capability	4.01	0.37	High

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Independent Variable	Mean	Standard Deviation (SD)	Implementation Level
Process Clarity	3.73	0.61	High
Return Policy Clarity	3.93	0.52	High
Overall	**4.07**	**0.66**	**High**

According to Table 3, the analysis of the implementation level of internal organizational factors shows that Technology Utilization received the highest mean score (M = 4.61, SD = 0.23), which is interpreted as "Highest". The Employee Capability variable had a mean score of 4.01 (SD = 0.37), indicating a "High" level of implementation, as did Process Clarity (M = 3.73, SD = 0.61) and Return Policy Clarity (M = 3.93, SD = 0.52). Overall, the average level of implementation across all variables was 4.07 (SD = 0.66), reflecting a generally high level of implementation.

Table 4 Distribution of Warehouses by Size

Warehouse Size	Number of Warehouses	Percentage (%)
Small	30	30
Medium	50	50
Large	20	20
Overall	**100**	**100**

According to Table 4, the largest proportion of the surveyed warehouses was medium-sized, totaling 50 warehouses (50%), followed by small-sized warehouses (30 warehouses, 30%) and large-sized warehouses (20 warehouses, 20%). In total, 100 warehouses were included in the survey, accounting for 100% of the sample.

Table 5 Distribution of Warehouses by Management Model

Management Model	Number of Warehouses	Percentage (%)
In-house	61	61
3PL	39	39
Overall	**100**	**100**

According to Table 5, most of the warehouses were managed in-house, with 61 warehouses (61%). Meanwhile, third-party logistics providers (3PLs) accounted for 39 warehouses (39%). All 100 warehouses were included in this study, representing 100% of the research sample.

Table 6 Analysis of the Implementation Level of Reverse Logistics Performance in E-commerce Warehouses in Nakhon Pathom Province

Dependent Variable	Mean	Standard Deviation (SD)	Level of Implementation
Return Cycle Time	3.78	0.65	High
Sorting Accuracy	4.02	0.51	High
Average Return Cost	3.35	0.72	Moderate
Customer Satisfaction	4.10	0.57	High
Overall	**3.81**	**0.74**	**High**

As shown in Table 6, the analysis of the implementation level of Reverse Logistics Performance in E-commerce warehouses in Nakhon Pathom Province revealed the following:

The variable Return Cycle Time had a mean score of 3.78 and a standard deviation of 0.65, indicating a high level of implementation.

The variable Sorting Accuracy scored a mean of 4.02 with a standard deviation of 0.51, also classified at the high level.

The variable Average Return Cost received a mean score of 3.35 and a standard deviation of 0.72, interpreted as a moderate level.

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The variable Customer Satisfaction regarding the return process had a mean of 4.10 and a standard deviation of 0.57, which is considered high.

Overall, the average score across all four dependent variables was 3.81 with a standard deviation of 0.74, reflecting an overall high level of Reverse Logistics Performance.

2. Analysis of the Influence of Factors on the Efficiency of Reverse Logistics in E-commerce Warehouses in Nakhon Pathom Province

Table 7 Multiple Regression Analysis to Predict the Influence of Factors on Reverse Logistics Performance in E-commerce Warehouses in Nakhon Pathom Province

Independent Variables	B	Std. Error	β	t	Sig.	VIF
Constant	-0.590	0.542		-1.087	0.280	
Technology Utilization (X1)	0.257	0.080	0.271	3.230*	0.002	1.088
Employee Capability (X2)	0.202	0.055	0.297	3.658*	0.000	1.012
Process Clarity (X3)	0.208	0.041	0.421	5.137*	0.000	1.039
Return Policy Clarity (X4)	0.175	0.060	0.241	2.945*	0.004	1.032
Medium Warehouse Size (D1)	0.143	0.067	0.122	2.134*	0.035	
Large Warehouse Size (D2)	0.198	0.079	0.161	2.506*	0.014	
3PL Management (D3)	-0.124	0.061	-0.108	-2.033*	0.045	

*Statistically significant at the 0.05 level

$R = 0.621$, $R^2 = 0.386$, Adjusted $R^2 = 0.360$, $F(4, 95) = 14.93$, $p < .05$

As presented in Table 7, the multiple regression analysis demonstrates that the model is statistically significant and suitable for predicting the efficiency of Reverse Logistics in E-commerce warehouses. The coefficient of determination (R^2) is 0.386, indicating that the model explains 38.6% of the variance in Reverse Logistics Performance, with an adjusted R^2 of 0.360, suggesting that the model remains accurate without overfitting.

The correlation coefficient (R) of 0.621 shows a moderate to high level of correlation between the independent variables and the dependent variable. The F-statistic ($F(4, 95) = 14.93$, $p < 0.05$) confirms that the overall regression model is statistically significant. The degrees of freedom in the F-statistic correspond to the four predictors entered into the model, after dummy coding categorical variables. Although seven variables are shown in Table 7, some were dummy-coded, and only non-reference categories were included in the analysis.

All independent variables were found to have a statistically significant influence ($p < 0.05$) on Reverse Logistics Performance. The relative strength of each factor, based on the standardized coefficients (β), is ranked as follows: Process Clarity ($\beta = 0.421$, $p = 0.000$), Employee Capability ($\beta = 0.297$, $p = 0.000$), Technology Utilization ($\beta = 0.271$, $p = 0.002$), Return Policy Clarity ($\beta = 0.241$, $p = 0.004$)

The unstandardized coefficients (B) for all variables are positive, indicating that an increase in the level of each factor contributes positively to the improvement of Reverse Logistics Performance.

In addition, the analysis shows that:

Warehouses of medium size (D1) and large size (D2) have a significantly higher level of performance compared to small-sized warehouses.

Warehouses using 3PL management (D3) showed a negative effect on performance compared to those managed in-house, as indicated by a negative coefficient ($B = -0.124$, $\beta = -0.108$, $p = 0.045$).

The Variance Inflation Factor (VIF) values range from 1.012 to 1.088, all well below the threshold of 5, indicating no multicollinearity issues among the independent variables.

Multiple Regression Equations

1. Unstandardized Coefficients Equation

$$Y = -0.590 + 0.257X_1 + 0.202X_2 + 0.208X_3 + 0.175X_4 + 0.143D_1 + 0.198D_2 - 0.124D_3$$

Where:

Y = Reverse Logistics Performance

Citation
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X_1 = Technology Utilization
X_2 = Employee Capability
X_3 = Process Clarity
X_4 = Return Policy Clarity
D_1 = Medium Warehouse Size (1 = Medium, 0 = Small)
D_2 = Large Warehouse Size (1 = Large, 0 = Small)
D_3 = 3PL Management (1 = 3PL, 0 = In-house)

2. Standardized Coefficients Equation

$$Z_Y = 0.271Z_{X1} + 0.297Z_{X2} + 0.421Z_{X3} + 0.241Z_{X4} + 0.122Z_{D1} + 0.161Z_{D2} - 0.108Z_{D3}$$

Where:

Z_Y = Standardized score of Reverse Logistics Performance
Z_{Xi} and Z_{Di} = Standardized scores of each independent variable

Discussion

The purpose of this multiple regression analysis was to examine the effects of internal organizational factors and warehouse characteristics on Reverse Logistics Performance using data from a sample of 100 E-commerce warehouses. The analysis results, as shown in the preceding table, indicated a correlation coefficient of R = 0.621, suggesting a moderate to high level of association between the set of independent variables and the dependent variable. The coefficient of determination (R^2) was 0.386, implying that the seven independent variables collectively explain 38.6% of the variance in Reverse Logistics Performance. According to Cohen's (1988) guidelines, this represents a medium to large effect size. The adjusted R^2 value of 0.360 further indicates the robustness of the model, showing minimal inflation from adding unnecessary predictors. Additionally, the model's significance was supported by an F-statistic of 14.93 with $p < .05$, confirming its statistical validity.

Effects of Independent Variables on Reverse Logistics Performance

1. Technology Utilization (X1)

With a coefficient of B = 0.257 and β = 0.271, this variable showed a statistically significant positive influence (p = 0.002) on Reverse Logistics Performance. This finding aligns with the studies of Issah et al. (2024) and Phunlarp et al. (2025), which emphasize that technologies such as RFID, WMS, and IoT help reduce processing time, minimize errors, and enable real-time tracking, thereby enhancing the efficiency of all stages in the return process. This finding supports the theoretical concept of supply chain visibility and automation, which are essential in reducing uncertainty and aligning with lean logistics principles.

2. Employee Capability (X2)

This factor had a coefficient of B = 0.202 and β = 0.297, indicating a strong influence (t = 3.658, p = 0.000). The finding is consistent with Mbago (2025) and Ramasamy & Anand (2024), who argue that organizations must invest in human capital through training, knowledge development, conflict resolution with customers, and complaint management—tasks that are increasingly complex in E-commerce environments. This aligns with the Resource-Based View (RBV), which sees human capital as a key source of competitive advantage in reverse logistics.

3. Process Clarity (X3)

Process Clarity showed the strongest influence in the model, with B = 0.208 and β = 0.421 (t = 5.137, p = 0.000). This result highlights the importance of having well-defined workflows, clear SOPs (Standard Operating Procedures), and internal tracking systems. It supports the work of Chaabane et al. (2024), who assert that eliminating ambiguity in logistics processes reduces operational errors and improves customer satisfaction. This result also reflects process management and lean thinking, where standardization and flow efficiency are critical.

4. Return Policy Clarity (X4)

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This variable had a coefficient of B = 0.175 and β = 0.241 (t = 2.945, p = 0.004), indicating that organizations with clear and transparent return policies—such as well-defined return periods, acceptance criteria, and compensation procedures—tend to achieve better performance in handling returns. This finding aligns with the studies by Amri et al. (2025) and Issah et al. (2024). From a customer service perspective, clear return policies contribute to supply chain transparency and improve customer trust.

Effects of Dummy Variables

5. Medium Warehouse Size (D1)

The coefficient B = 0.143 and β = 0.122 (p = 0.035) suggest that, compared to small warehouses, medium-sized warehouses are slightly more efficient in handling returns. This may be due to the availability of more resources and space, which facilitates more systematic operations. This reflects principles from logistics network design, where medium-scale facilities balance flexibility and resource availability.

6. Large Warehouse Size (D2)

This variable demonstrated a more pronounced positive effect, with B = 0.198 and β = 0.161 (p = 0.014). Warehouses classified as large generally have superior technological capabilities, infrastructure, and staffing. This finding is consistent with Sarkar, Bhattacharya, & Sarkar (2025), who point out that economies of scale in larger warehouses enhance their ability to manage returns more effectively. This result is consistent with the theory of economies of scale, which suggests that larger facilities can reduce per-unit return handling costs.

7. 3PL Management (D3)

The coefficient for 3PL (Third-Party Logistics) management was B = -0.124 and β = -0.108 (p = 0.045), indicating a negative effect on Reverse Logistics Performance when compared to in-house management. This may stem from 3PL providers' limitations in responding to company-specific return policies or their lack of control over critical processes. The result supports the studies of Haddad & Bhat (2025) and Mourya (2025), which suggest that firms relying on 3PL for warehouse operations may encounter challenges in information control, agility, and responsiveness to urgent return-related events. This aligns with Transaction Cost Economics and Agency Theory, which highlight potential inefficiencies due to outsourcing-specific, high-control processes like reverse logistics.

Conclusion

This study aimed to examine the internal organizational factors and warehouse characteristics that influence the efficiency of Reverse Logistics in E-commerce warehouses located in Nakhon Pathom Province. Data were collected from a sample of 100 warehouses, and the analysis was conducted using Multiple Regression Analysis to assess the influence of seven independent variables: Technology Utilization, Employee Capability, Process Clarity, Return Policy Clarity, and Warehouse Characteristics (categorized as medium and large warehouse size), as well as Warehouse Management Model (in-house versus 3PL). This study contributes to the growing body of reverse logistics literature by offering empirical evidence from a provincial logistics hub in Thailand. The insights derived from E-commerce warehouses in Nakhon Pathom provide a nuanced understanding of how local operational structures affect reverse logistics performance, filling a gap in current studies that often focus on metropolitan or global logistics contexts.

The results indicated that the model was statistically significant (F = 14.93, $p < 0.001$), and the independent variables collectively explained 38.6% of the variance in Reverse Logistics Performance (R^2 = 0.386), which is considered a moderate-to-high level of effect. No multicollinearity issues were detected, as all VIF values ranged from 1.012 to 1.088, which is within the acceptable range.

Among the predictors, Process Clarity emerged as the most influential factor (β = 0.421, $p < 0.001$), underscoring the importance of systematic workflows, written standard operating procedures (SOPs), and shared understanding among employees. These elements significantly enhance the effectiveness of return operations. The second most influential factor was Employee Capability (β = 0.297, $p < 0.001$), highlighting the critical role of knowledgeable and skilled personnel in managing, inspecting, and communicating during

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the return process. Technology Utilization ($\beta = 0.271$, $p = 0.002$) was also significant, emphasizing the role of advanced technologies in automating return processes, improving accuracy, and reducing processing time.

In addition, Return Policy Clarity had a statistically significant influence ($\beta = 0.241$, $p = 0.004$). Organizations with well-defined return policies, such as clear timelines, procedures, and compensation criteria, were more likely to improve customer satisfaction and reduce unnecessary errors or disputes.

Regarding warehouse characteristics (analyzed as dummy variables), medium-sized warehouses (D1: $\beta = 0.122$, $p = 0.035$) and large-sized warehouses (D2: $\beta = 0.161$, $p = 0.014$) were found to positively impact reverse logistics performance when compared to small warehouses. This suggests that larger facilities tend to have more resources and systems that support efficient return management. However, the use of third-party logistics providers (3PL) (D3: $\beta = -0.108$, $p = 0.045$) showed a negative effect compared to in-house management, potentially due to limited control over return processes and reduced responsiveness to organization-specific policies.

Based on these findings, the study concludes that enhancing the efficiency of Reverse Logistics requires an integrated focus on process structure, personnel capability, and technology adoption, along with strategic decisions about warehouse size and management models tailored to the organization's context. This comprehensive approach will enable firms to better meet customer expectations, reduce losses, and strengthen their long-term competitiveness in the E-commerce sector sustainably. Practically, firms are encouraged to adopt integrated Warehouse Management Systems (WMS) with return modules, invest in automated sorting systems, and establish routine training programs for return handling and customer service. For firms working with 3PL providers, contract design should emphasize alignment in return processes and include clear service-level agreements (SLAs) to ensure control and responsiveness.

Recommendation

1. Practical Recommendations

1.1 Enhance the Clarity of Return Processes

Given that *Process Clarity* had the strongest impact, organizations should implement clear SOPs covering each return stage. Integrating real-time tracking systems will ensure consistency, reduce ambiguity, and minimize errors throughout the process.

1.2 Continuously Develop Employee Capability

Ongoing training should focus on product inspection, complaint handling, customer interaction, and system usage. Investing in human capital ensures higher operational efficiency and responsiveness.

1.3 Invest in and Integrate Technology into the Return Process

Firms should adopt WMS, barcode/QR code scanning, RFID, and AI-powered analytics to streamline return workflows, reduce turnaround time, and increase accuracy.

1.4 Review and Redesign Return Policies

Return policies must be transparent and adaptable, with clear timeframes, item conditions, and compensation guidelines. This builds trust and supports seamless return experiences.

1.5 Select Appropriate Warehouse Size and Management Model

Since medium and large warehouses showed better performance, firms should assess whether current facilities align with their return volumes. Expansion or reinvestment may be necessary to support scalable operations.

1.6 Evaluate Third-Party Logistics (3PL) Suitability

As 3PL usage showed negative effects, businesses should review their providers' capacity to align with internal standards. Where misalignment persists, reintegrating returns into in-house operations may offer better control and agility.

2. Recommendations for Future Research

2.1 Explore Causal Relationships through Experimental Designs

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Future research should consider experimental or quasi-experimental designs to establish causal relationships between internal organizational factors and reverse logistics performance. This would enhance methodological rigor beyond correlational analysis and support stronger managerial implications.

2.2 Broaden the Research Context

To enhance generalizability, future studies should examine reverse logistics in different regional contexts, such as Eastern or Southern Thailand, or across various business models (e.g., B2B vs. B2C). Comparative analysis would reveal how contextual variables influence operational outcomes.

2.3 Integrate External Influencing Factors

Incorporating external variables such as customer expectations, regulatory constraints, or competitive intensity could provide a more holistic understanding of return logistics. This aligns with open-systems theory, which emphasizes the role of environmental influences on internal processes.

2.4 Evaluate Economic Viability of Return Technologies

Future research should assess the cost–benefit trade-offs of implementing automated return technologies (e.g., WMS-integrated platforms, AI-enabled sorting). Such analysis supports strategic investment decisions and contributes to the financial dimension of logistics efficiency.

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