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Reverse Process Effectiveness as a Mediator of Return Volume Uncertainty, Return Information Quality, and Return Decision Quality on Warehouse Operational Performance in Indonesian FMCG Companies

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Abstract: In fast-moving consumer goods (FMCG) warehouses, product returns arrive largely unplanned and in unpredictable volumes, yet practice has outpaced academic understanding of how such uncertainty affects operations. Prior studies disagree on how return volume uncertainty, return information quality, and return decision quality shape warehouse operational performance, and the mediating role of reverse process effectiveness remains unconfirmed, particularly in Indonesian FMCG warehouses. This study tests the direct and indirect effects of these three antecedents on warehouse operational performance, with reverse process effectiveness as mediator. Data were collected from 138 warehouse staff, supervisors, and managers at Indonesian FMCG companies through a cross-sectional survey and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Results show that return information quality directly improves warehouse operational performance, while return volume uncertainty and return decision quality affect performance only indirectly, through reverse process effectiveness. The novelty of this study is that reverse process effectiveness is not a peripheral outcome but the mechanism that converts information quality, decision quality, and volume-uncertainty management into measurable performance gains, giving warehouse managers a clear operational priority: investing in reverse process capability yields the broadest performance returns.

Keyword: Return Volume Uncertainty, Return Information Quality, Return Decision Quality, Reverse Process Effectiveness, Warehouse Operational Performance.

INTRODUCTION

As ecommerce and omnichannel trade continue to flourish, a perennial issue for which practitioners have struggled to find academic assistance is return shipments showing up unannounced and in quantities that no one can really predict. Warehouses act as a buffer. In the past, reverse logistics was limited to the act of cleaning up after a sale was made; today, it can become a pillar of a firm's cohesion when its value chains are under stress, and it is becoming more and more important to include it as a part of a firm's logistics social responsibility (Biancolin et al., 2023). In FMCG warehouse this is the most challenging, because FMCG products are moving quickly, have a short shelf life and returns that show little discernible pattern.

(Suwignjo et al., 2023) investigated one of the largest FMCG companies in Indonesia and discovered that the demand and return of the products fluctuate without any pattern, resulting in frequent changes in inventory decision-making made by the warehouse staff. This type of irregularity directly affects the performance of FMCG transport and warehousing (Chauhan et al., 2023). However, (Makaleng & Hove-Sibanda, 2022) were more optimistic and believed that companies that incorporate their reverse logistics strategy can turn the challenge into a competitive advantage. In the context of Indonesian e-commerce, (Prayogo et al., 2024) identified one key element that stands out when it comes to effective return handling clarity of return policy, which signifies more than just the speed of returns processing.

An FMCG company in Indonesia maintains return incident reports (Berita Acara Return), and the March-June 2026 records indicate that it is not just a picture, but a pattern, 16,195 return transactions, or in total there are 91,952 cartons (Cs). The number of transactions moved very little month to month, switching between 17,303 Cs in June and 32,295 Cs in March, a coefficient of variation of 24.9% and a peak to trough swing of 86.6%.

(CV of 5.2%). Return events, that is, occur at a relatively regular rate; what their size is, no one can be pinned down, and that's what return volume uncertainty is, as articulated in Organizational Information Processing Theory, OIPT (Galbraith, 1974). The monthly amounts are presented in Table 1.

Table 1 Monthly Summary of Company Return Data, March-June 2026

Month	Return Transactions	Return Volume (Cs)	Damaged/Lost (Pcs)	% Caused by Manufacturing/CS
March	3,949	32,295	115	56.9%
April	3,918	19,510	205	57.8%
May	4,415	22,844	219	59.6%
June	3,913	17,303	109	63.7%
Total / Average	16,195	91,952	648	59.5%

Source: Company Return Incident Reports (Berita Acara Return), March-June 2026, processed by the researcher.

The statistics are even more stark when broken out by person in charge. Quality issues that can be attributed to the manufacturing/production division, such as leaking packaging, broken bottle caps, dented cans, make up 59.5% of all 16,195 transactions. Another 29.4% is due to order administration errors at the customer service/order-entry level. Hereby, the warehouse itself only makes 2.2% of the errors. Conduct a Pareto Analysis, and one cause stands above the rest: store reject due to leakage, pouch defect or bottle-cap problem, which accounts for 46.1% of all returns reported. We find that damaged or lost units have been swinging as vigorously as ever, from 109 units in June to 219 in May (CV of 31.0%, swing of 100.9%), implying that the effectiveness of the reverse process has not been consistent month-to-month; otherwise unmanaged, that inconsistent swing risks leakage of real value, as (Wofuru-Nyenke et al., 2023) have explained. But there's a regional dimension to all of this, as Jabodetabek alone represented 54.7% of all transactions.

The first coherent theoretical underpinning of reverse logistics was provided by (Rogers et al., 1998) who pointed out the back flow of product through a supply chain. On this premise, Organizational Information Processing Theory further posits that when operational uncertainty exceeds an organization's ability to process information, operational certainty returns as a factor of information processing then performance worsens (Galbraith, 1974; Appiah & Owusu-Bio, 2024). However, few studies have examined the interaction between return volume uncertainty, return information quality, return decision quality against warehouse operational performance with the mediator of reverse process effectiveness, and none have examined the interaction in Indonesian FMCG warehouse.

The empirical gap that this study fills is not a theoretical gap; rather, researchers continually arrive at divergent findings instead of failing to research the topic. Consider return volume uncertainty. Under their guidance (Suwignjo et al., 2023) it is possible to be managed without impacting performance, but it is necessary for a company to have a good predictive analytics. The contrary results were reported in (Akın Ateş et al., 2022; Ponte et al., 2020) underlining that uncertainty has a severe negative impact on performance, via bullwhip and increased supply chain complexity. Researchers were divided regarding information and decision quality. (Božić et al., 2024; Kankam et al., 2023) identified a direct and significant relationship between information and data quality and process performance, whereas (Karlsson et al., 2023; Prayogo et al., 2024) found no such direct link, reporting only an indirect relationship that runs through other mediators. A similar divide appears in the literature on decision quality: (Bag et al., 2021; Ropi et al., 2021) found that standardized return decisions do not necessarily translate into better performance, since consumer preferences and manager behaviour are too diverse to be captured by uniform decision rules. Even though there is some disagreement about the mediating role of reverse process effectiveness, it is still widely accepted as an important pathway (Adeodu et al., 2023; Putri Mawadi et al., 2023).

This does not mean that the theory is missing or that they have never been studied before, Indonesian FMCG warehouses have been studied before by (Ambilkar et al., 2022; Che Hassan & Osman, 2025; Gallegos et al., 2024) just not frequently. What this study proposes to do is a re-test: combine return volume uncertainty, return information quality and return decision quality into one model and examine the direct and indirect impacts on warehouse operational performance by applying reverse logistics theory (Rogers et al., 1998) and OIPT (Galbraith, 1974) to explain whatever the outcome of the results may be.

Based on this description, the research problem can be formulated as follows:

1. Does return volume uncertainty have a direct and positive effect on warehouse operational performance?
2. Does return information quality have a direct and positive effect on warehouse operational performance?
3. Does return decision quality have a direct and positive effect on warehouse operational performance?
4. Does reverse process effectiveness have a direct and positive effect on warehouse operational performance?
5. Does return volume uncertainty have a direct and positive effect on reverse process effectiveness?
6. Does return information quality have a direct and positive effect on reverse process effectiveness?
7. Does return decision quality have a direct and positive effect on reverse process effectiveness?
8. Does reverse process effectiveness mediate the effect of return volume uncertainty on warehouse operational performance?
9. Does reverse process effectiveness mediate the effect of return information quality on warehouse operational performance?
10. Does reverse process effectiveness mediate the effect of return decision quality on warehouse operational performance?

METHOD

This research used a quantitative cross sectional method in order to examine the hypothesized causal relationships (Sekaran & Wiley, 2003). Modeling (PLS-SEM) was used to test the proposed research model. The research is located in FMCG companies that have their own internal warehouse divisions for managing their own RL and the respondents are staff, supervisors and managers that are directly involved in the receiving, inspection, sorting and disposition decision of returned products. The model examines the relationship between Return Volume Uncertainty (X1), Return Information Quality (X2), Return Decision Quality (X3) and Warehouse Operational Performance (Y) both directly and indirectly via Reverse Process Effectiveness (Z) (Sari et al., 2022; Hair et al., 2021) ; The research is grounded in the theory of reverse logistics (Rogers et al., 1998) and OIPT (Galbraith, 1974) which are used throughout the research.

The population includes all employees who work directly with returned products, whether a staff, supervisor, or manager, in FMCG companies in Indonesia. There is no known population size, therefore, non-probability sampling (purposive) was used where the respondents were chosen from the population according to the study's criteria. Recommended number of indicators for PLS-SEM is 5-10 times the indicators (Hair et al., 2021); here this results in the target range of 100-200 respondents with 20 reflective indicators. Data collection resulted in 138 respondents (85.71% of 161), and after screening, a total of 23 of those who responded failed to meet the criteria, leaving 138 as the final sample.

The two data-collection methods were conducted concurrently: the literature review on Return Volume Uncertainty, Return Information Quality, Return Decision Quality, Reverse Process Effectiveness, and Warehouse Operational Performance, mainly based on OIPT (Galbraith, 1974) ; and the online questionnaire based on a semantic differential scale adapted from previous studies to reflect respondent perceptions (Hardani et al., 2020). The primary data was obtained by filling out google form questionnaires by the staff, supervisor and manager of the FMCG in Indonesia who are directly in charge of returns.

Validity and reliability were tested by SmartPLS. Convergent validity is measured by the factor loading of each indicator (not less than 0.70) and the AVE of each indicator (not less than 0.50), while the discriminant validity is based on the Fornell-Larcker criterion and cross loading, supplemented by the HTMT with values less than 0.90 (Hair et al., 2021). Reliability is based on Cronbach's Alpha, Composite Reliability and rho_A, which must meet the criterion of 0.70.

The analysis was performed using the entire sample, as PLS-SEM is capable of analyzing multiple latent variables and mediation irrespective of normal data and a large sample size (Hair et al., 2021) and was conducted using the software SmartPLS. The three stages were: outer model, testing validity and reliability; inner model, testing R-Square and path significance with 5,000 bootstrap resamples at $p < 0.05$; and mediation test for Reverse Process Effectiveness using bootstrapped indirect effects. When measurement quality scores good, R^2 is greater than 0.50, and relationships are significant ($p < 0.05$). The following framework (Figure 1) brings together the phenomenon, the research gap and the novelty mentioned above.

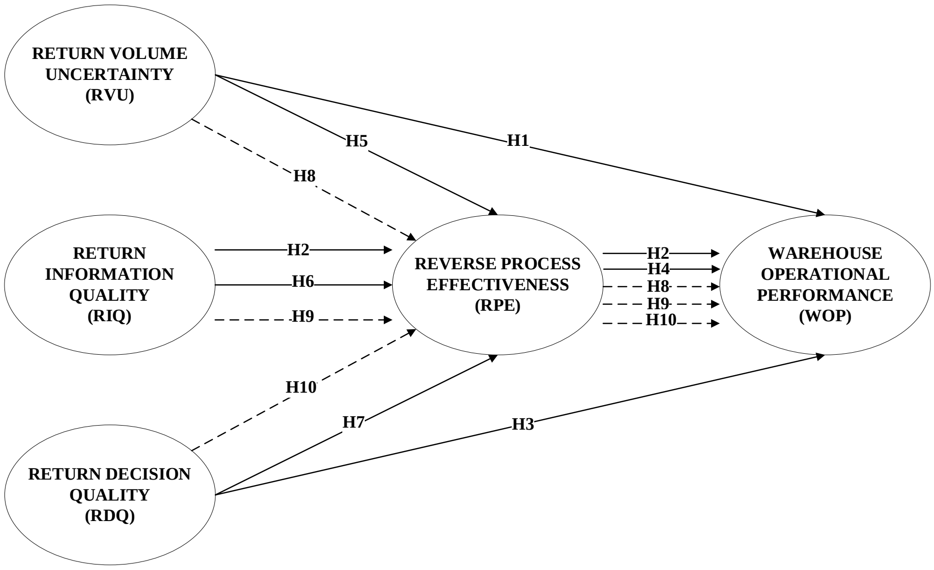

Figure 1 Conceptual Framework

Information:
- : Direct Influence (H1, H2, H3, H4, H5, H6, H7)
- : The Influence of Mediation (H8, H9, H10)

RESULTS AND DISCUSSION

Result

Respondent Characteristics

Of the 161 respondents who completed the survey, 138 met the screening criteria and formed the final sample; 23 failed the screening criteria and were excluded for a 85.71% participation rate (138/161). Table 2 reveals that the workforce is heavily male-dominated (86.2%), over 40 years old (71.0%), with a bachelor's degree (63.8%), more than 10 years of experience (60.1%), working in operational-staff position (47.1%) and predominantly in FMCG businesses (43.5%). When combined, these numbers represent a respondent pool whose hands-on experience in return handling means that their answers are given some credibility that they represent actual warehouse conditions and not an educated guess.

Table 2 Respondent Characteristics (n = 138)

Category	Classification	Frequency	Percentage
Gender	Male	119	86.2%
	Female	19	13.8%
Age	20-25 years	4	2.9%
	26-30 years	12	8.7%
	31-35 years	5	3.6%
	36-40 years	19	13.8%
	> 40 years	98	71.0%
Last Education	Senior/Vocational High School	17	12.3%
	Diploma (D3/D4)	19	13.8%
	Bachelor's Degree (S1)	88	63.8%
	Master's Degree (S2)	11	8.0%
	Doctoral Degree (S3)	3	2.2%
Work Tenure	< 1 year	3	2.2%
	1-3 years	23	16.7%
	4-6 years	11	8.0%
	7-10 years	18	13.0%

Category	Classification	Frequency	Percentage
	> 10 years	83	60.1%
Position	Manager / Director	52	37.7%
	Supervisor	17	12.3%
	Operational Staff	65	47.1%
	Support Staff (Non-Operational)	4	2.9%
Company Industry	FMCG (Food, Beverage, Dairy, etc.)	60	43.5%
	Personal Care / Home Care	28	20.3%
	Household Product	23	16.7%
	Pharmaceutical	14	10.1%
	Logistics / Warehouse & Distribution	10	7.2%
	Other (Agriculture, Supply Chain, etc.)	3	2.2%

Source: Primary data, processed by the researcher (2026).

Evaluation of the Measurement Model (Outer Model)

The outer loading for each indicator is the basis of convergent validity where 0.70 is a threshold for a valid indicator (Hair et al., 2021). All indicators in the five variables above this are between 0.800 and 0.932 in Table 3, and each indicator is consistent with its intended construct.

Table 3 Outer Loading Results

Indicator	RVU (X1)	RIQ (X2)	RDQ (X3)	RPE (Z)	WOP (Y)
X1.1	0.855				
X1.2	0.844				
X1.3	0.868				
X1.4	0.888				
X2.1		0.842			
X2.2		0.884			
X2.3		0.901			
X2.4		0.860			
X3.1			0.911		
X3.2			0.919		
X3.3			0.932		
X3.4			0.895		
Z1				0.922	
Z2				0.879	
Z3				0.908	
Z4				0.876	
Y1					0.800
Y2					0.899
Y3					0.864
Y4					0.887

Source: SmartPLS output, processed by the researcher (2026).

A variable is regarded as valid if the square root of the AVE (displayed on the diagonal) exceeds the correlation between the variable and each of the other variables (Hair et al., 2021). which is defined as the Fornell-Larcker criterion. Table 4 supports this for each of the five variables; Return Volume Uncertainty, Return Information Quality, Return Decision Quality, Reverse Process Effectiveness and Warehouse Operational Performance are each discriminantly distinct.

Table 4 Fornell-Larcker Discriminant Validity

	RVU	RIQ	RDQ	RPE	WOP
RVU	0.864				
RIQ	0.559	0.872			
RDQ	0.570	0.725	0.915		
RPE	0.679	0.704	0.772	0.897	
WOP	0.569	0.706	0.584	0.715	0.863

Source: SmartPLS output, processed by the researcher (2026).

Reliability includes Cronbach's Alpha, rho_A, Composite Reliability and AVE; a variable is reliable when Composite Reliability is above 0.70 and AVE is above 0.50 (Hair et al., 2021). Table 5 shows every variable passing comfortably: Cronbach's Alpha runs 0.886 to 0.935, rho_A runs 0.891 to 0.937, Composite Reliability runs 0.921 to 0.953, and AVE runs 0.745 to 0.836.

Table 5 Reliability and Average Variance Extracted (AVE)

Variable	Cronbach's Alpha	rho_A	Composite Reliability	AVE
RVU	0.887	0.891	0.922	0.746
RIQ	0.895	0.895	0.927	0.760
RDQ	0.935	0.937	0.953	0.836
RPE	0.919	0.921	0.943	0.804
WOP	0.886	0.893	0.921	0.745

Source: SmartPLS output, processed by the researcher (2026).

The overall results of the measurement model testing are presented in the figure below in Figure 2.

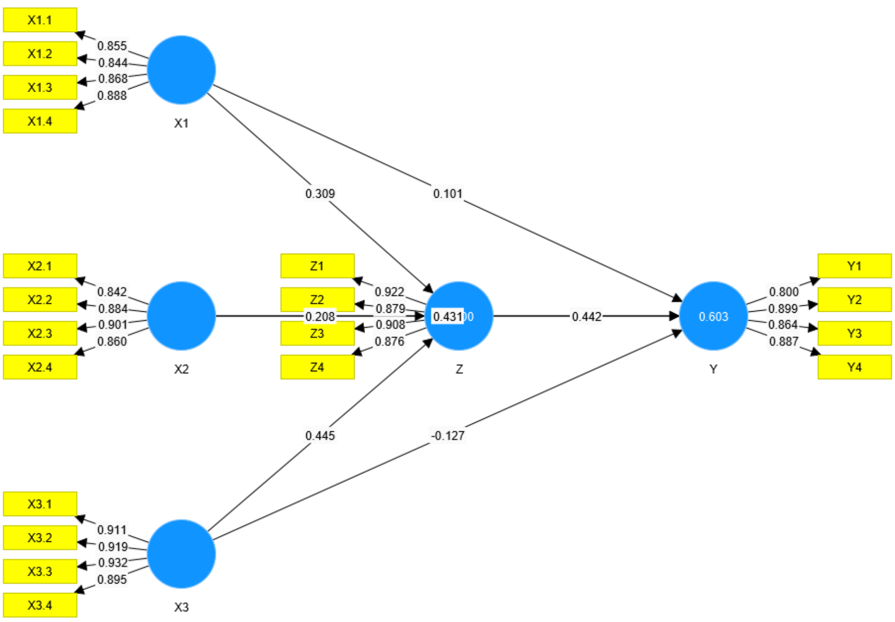

Figure 2 Full Outer Model

From the results of the full outer model shown in the figure, it can be seen that all the outer loading values of the research variables are more than 0.7. So that it can be concluded that all indicators are valid and can be used in the study.

Structural Model Test Results (Inner Model)

R-Square (R^2) indicates the amount of variance in the dependent variable explained by the model with a perfect fit being 1, a strong fit being 0.75, a moderate fit being 0.50 and a weak fit being 0.25 Hair et al. (2021). Table 6 shows that the R2 value of Reverse Process Effectiveness (Z) is 0.700, which is a good R2 value, indicating that together Return Volume Uncertainty (X1), Return Information Quality (X2) and Return Decision Quality (X3) can explain 70.0% of the variance of the effectiveness of the reverse process. The results of Warehouse Operational Performance (Y) in the moderate-to-strong range are 0.603, while the variance explained by the four factors (X1, X2, X3 and Z) is 60.3%.

Table 6 R-Square Results

Variable	R Square	R Square Adjusted
RPE (Z)	0.700	0.694
WOP (Y)	0.603	0.591

Source: SmartPLS output, processed by the researcher (2026).

Path-coefficient significance was determined by testing with 5,000 resamples using bootstrapping and a level of significance of $p<0.05$ at 95% confidence (Hair et al., 2021). The results of the seven direct-effect hypotheses are presented in Table 7 and in Figure 3.

Table 7 Hypothesis Testing - Path Coefficients (Direct Effects)

Path	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics	P Values	Decision
X1 -> Y (H1)	0.101	0.107	0.085	1.181	0.238	Not Supported
X2 -> Y (H2)	0.431	0.429	0.072	5.947	0.000	Supported
X3 -> Y (H3)	-0.127	-0.116	0.115	1.112	0.267	Not Supported
Z -> Y (H4)	0.442	0.430	0.109	4.054	0.000	Supported
X1 -> Z (H5)	0.309	0.314	0.061	5.028	0.000	Supported
X2 -> Z (H6)	0.208	0.203	0.068	3.054	0.002	Supported
X3 -> Z (H7)	0.445	0.448	0.075	5.924	0.000	Supported

Source: SmartPLS bootstrapping output, processed by the researcher (2026).

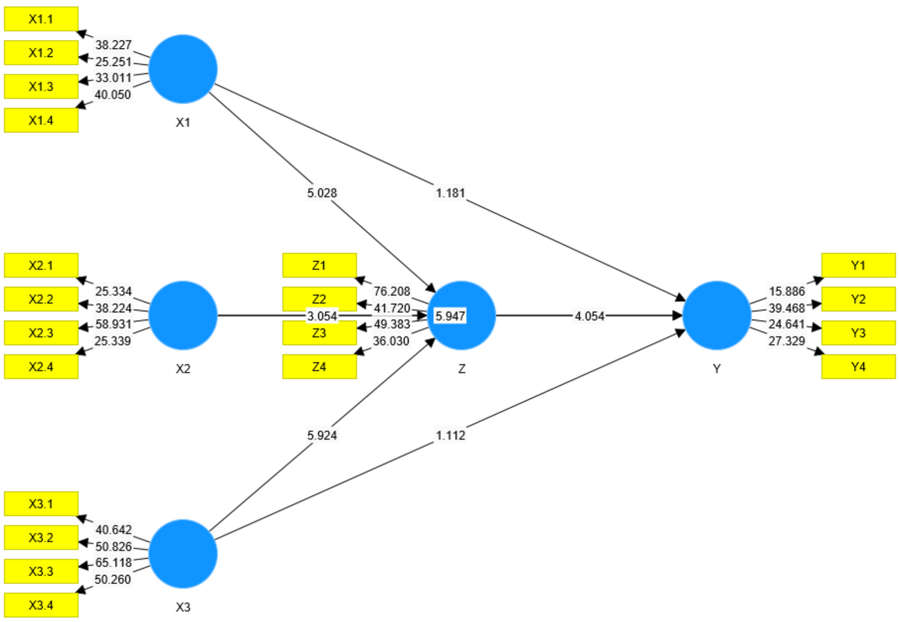

Figure 3 Bootstrapping Results

There was no significant relationship between Return Volume Uncertainty and Warehouse Operational Performance (beta = 0.101; t = 1.181; p = 0.238 > 0.05); H1 is rejected. Return Information Quality cleared it with a positive effect (beta = 0.431; t = 5.947; p = 0.000 < 0.05); H2 stands. Return Decision Quality also missed, and its direction even turned negative (beta = -0.127; t = 1.112; p = 0.267 > 0.05); H3 is rejected too. The RPE was found to have a positive, significant effect on performance (beta = 0.442; t = 4.054; p = 0.000 < 0.05) and H4 is supported. Moving to the antecedents of Reverse Process Effectiveness Return Volume Uncertainty had a positive and significant effect (beta = 0.309; t = 5.028; p = 0.000 < 0.05) as did Return Information Quality (beta = 0.208; t = 3.054; p = 0.002 < 0.05); H5 and H6 are supported. Return Decision Quality had the highest coefficient of all the variables in the entire model (beta = 0.445; t = 5.924; p = 0.000 < 0.05) and it supported H7 and is the strongest factor in the model predicting Reverse Process Effectiveness.

A mediation test was conducted to determine if Reverse Process Effectiveness (Z) is in between Return Volume Uncertainty (X1), Return Information Quality (X2), Return Decision Quality (X3) and Warehouse Operational Performance (Y). Table 8 provides details of the specific indirect effects.

Table 8 Mediation Testing - Specific Indirect Effects

Path	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics	P Values
X1 -> Z -> Y (H8)	0.137	0.134	0.041	3.338	0.001
X2 -> Z -> Y (H9)	0.092	0.088	0.041	2.271	0.024
X3 -> Z -> Y (H10)	0.197	0.191	0.055	3.597	0.000

Source: SmartPLS bootstrapping output, processed by the researcher (2026).

The Return Volume Uncertainty to Warehouse Operational Performance relationship is significant and is mediated by Reverse Process Effectiveness (beta = 0.137; t = 3.338; p = 0.001 < 0.05); H8 is supported. Because the direct path (H1) is not successful but the indirect path (H2) is successful, this is considered as full mediation, return volume uncertainty is only achieved through the intermediate link of reverse process effectiveness. The Return Information Quality link also is significant (beta = 0.092; t = 2.271; p = 0.024 < 0.05); H9 stands, and given that the direct link (H2) is also successful, this is a partial mediation, where information quality not only stands alone, but also strengthens the process. Return Decision Quality also mediates significantly too (beta = 0.197; t = 3.597; p = 0.000 < 0.05); H10 still holds and since H3 is not significant, it is also full mediation, meaning that Return Decision Quality only pays off when it is translated to a more effective reverse logistics process.

Discussion

Each hypothesis is discussed, interpreting the empirical results in relation to the relevant theories and studies, and highlighting their implications on reverse logistics and warehouse operational performance.

1. **Return Volume Uncertainty on Warehouse Operational Performance.**
   This path was not significant (beta = 0.101; p = 0.238), contrary to a naïve interpretation of OIPT: higher uncertainty should lead to lower performance, unless it is absorbed by something. However, this finding was not expected as volume swings have been shown to have the negative impact through bullwhip effects (Akın Ateş et al., 2022) and in closed-loop supply chains (Ponte et al., 2020). The more likely interpretation is that, once a company develops mitigation plans that don't depend on volume per se, disruption no longer results in a productivity loss, as described by (Hasan et al., 2023). Return volume fluctuation, by itself, is neither good nor bad. It is how the warehouse absorbs that volume through the reverse logistics process that is the variable, and that is Reverse Process Effectiveness. A more critical reading is that OIPT predicts a performance penalty only

when uncertainty outstrips an organization's information-processing capacity; in the sampled warehouses, monthly-level return volume, tracked through recurring incident reports and routine reconciliation, may sit within a band that existing information-processing routines can already absorb, so the strain never reaches the threshold at which it would show up as a direct performance loss. This does not make volume uncertainty irrelevant, it relocates its effect upstream, into the process capability that determines whether that absorption happens smoothly or at a hidden cost, which is precisely what the full mediation reported under H8 later confirms.

2. **Return Information Quality on Warehouse Operational Performance.**
This was the largest and most significant (beta = 0.431; p = 0.000) direct path to performance that entered the model. This trend was also evident for FMCG distribution and retail companies, where product master data quality directly contributed to logistics process performance (Božić et al., 2024) and in the broader supply chain, where information quality led to better logistics process performance, but only when accompanied by active information sharing among processes or departments (Kankam et al., 2023). The mechanism is not hard to picture: accurate batch numbers, production dates, and return reasons cut down the guesswork that normally slows a warehouse team down.

3. **Return Decision Quality on Warehouse Operational Performance.**
Here nothing significant was found and the direction was even slightly negative (beta = -0.127; p = 0.267). One explanation is that managers frequently take decisions that deviate from the profit-maximising benchmark and that the quality of the decisions on paper doesn't necessarily reflect the quality of the decisions when executed (Oh et al., 2024). Consumer preferences towards return policy differ across segments, which further complicates the matter (Abdulla et al., 2022). The latter (Kalubanga & Mbekeka, 2023) take it one step further by demonstrating how policy compliance only enhances performance if it is implemented uniformly in all operational lines, a fact that is not always the case. The "quality of the decision" is crucial, but it must also be translated into a working process in order to be manifested as better performance in the warehouse, and this is exactly what the mediation results below confirm. A more critical explanation is that decision quality, as measured here, captures the soundness of a disposition call at the moment it is made, accept, reject, salvage, write-off, rather than how consistently and quickly that call is executed afterward. A technically sound decision that sits in an approval queue, waits on cross-departmental sign-off, or is applied unevenly across shifts delivers none of its intended benefit to the warehouse floor; the benefit only materializes once the decision is carried through a working reverse process. Read this way, the near-zero and slightly negative direct path is not a contradiction of decision-quality theory but a boundary condition of it: decision quality is a necessary input whose performance payoff is conditional on process execution, not an independent driver in its own right.

4. **Reverse Process Effectiveness on Warehouse Operational Performance.**
This path came through significant and positive (beta = 0.442; p = 0.000), the largest direct driver of Warehouse Operational Performance in the model. (Chauhan et al., 2023) reported the same relationship among FMCG managers and executives, where optimized transportation and warehousing performance lifted overall distribution outcomes, and (Makaleng & Hove-Sibanda, 2022) found reverse logistics strategy driving competitiveness among FMCG retailers in South Africa. Cycle speed, cost efficiency, execution reliability, and adaptability to shifting volume or stakeholder demands appear to matter most.

5. **Return Volume Uncertainty on Reverse Process Effectiveness.**
This path was positive and significant (beta = 0.309; p = 0.000), reading almost like the opposite of H1: uncertainty does not sit idle; it pushes the process to adapt. (Nanayakkara et al., 2022) built a circular reverse logistics framework around this idea, showing geographic clustering of return patterns can optimize a network even when volume swings sharply. (K. A. Khan et al., 2024). In this reading, information quality is more raw material than finished product: it provides something accurate to work with, but the process still has to work to make it into faster cycles and lower costs, which may be why this was not as far ahead as the other two predictors of process effectiveness.

6. **Return Information Quality on Reverse Process Effectiveness.**
However, also positive, significant (beta = 0.208; p = 0.002), albeit the smallest of the three coefficients that lead in to Reverse Process Effectiveness. Strong data-generation and integration capability was found to be correlated to better strategic and tactical reverse logistics decisions among South African manufacturers (Bag et al., 2021) and big data analytics was observed to improve return-process effectiveness for SMEs with closed-loop supply chains (S. A. R. Khan et al., 2024) found big-data analytics improving return-process effectiveness among SMEs working with closed-loop supply chains. Information quality, in this reading, functions as raw material rather than finished product: it gives the process something accurate to work with, but the process still has to do the work of turning that information into faster cycles and lower costs, which likely explains why this path, while significant, trails behind the other two predictors of process effectiveness.

7. **Return Decision Quality on Reverse Process Effectiveness.**
This path had the greatest coefficient of all paths in the model (beta = 0.445; p = 0.000), compared with both return volume uncertainty and return information quality as a predictor of process effectiveness. (Makaleng & Hove-Sibanda, 2022) identified resource-allocation decisions and top-management backing as factors that drive competitive advantage in reverse logistics; and (Karlsson et al., 2023) demonstrated that return-policy decisions, aligned with operational capability, lead to a more effective handling process. Decision-making, speed of eligibility confirmation, regularity of policy application, speed of accounting sign-off sets the tone for the whole process, more so than the sheer volume of information or pressure from volume alone.

8. **Reverse Process Effectiveness mediating Return Volume Uncertainty on Warehouse Operational Performance.**
This is true of full mediation (beta = 0.137; p = 0.001): mediation was successful but the direct path was not (H1 was not supported). A similar conclusion was reached in (Ropi et al., 2021) on remanufacturing uncertainty: decision-support methods tailored to cope with volume fluctuations can either save or burn money. However, they showed that the same pathway remained valid even in the presence of genuine volatility (Saruchera & Asante-Darko, 2021) warn that such process improvements are likely to be context-specific (Adeodu et al., 2023).

9. **Reverse Process Effectiveness mediating Return Information Quality on Warehouse Operational Performance.**
The effect of this predictor (beta = 0.092; p = 0.024) is different from the other two predictors, because information quality is not only indirectly related to performance through its relationship to user satisfaction (H3), but is directly related as well (H2).

(Appiah & Owusu-Bio, 2024) identified a corresponding dual effect with the analytics capability producing quality information that supported the reverse logistics process and also had a direct impact on financial performance. (Božić et al., 2024) added that data quality has a direct effect on logistics performance and that data quality will produce an improvement in operational processes, which is essentially the same as here.

10. **Reverse Process Effectiveness mediating Return Decision Quality on Warehouse Operational Performance.**
    Full mediation also has this effect (beta = 0.197; p = 0.000), the strongest indirect effect of the three, and, in conjunction with the null (H3) direct path, provides additional support for the idea that the impact of decision quality is only seen in performance when it is implemented in the process. Prioritising return-handling effectiveness is located between the governance and customer-facing outcomes as found by (Prayogo et al., 2024) and strategic decision factors acted as a connective bridge between reverse logistics governance and firm performance as found by (Foo & Abdul Jalil, 2021). Since the direct effect of Return Decision Quality on Reverse Process Effectiveness was also found to be the strongest in H7, this is the single most important lever in the model, if harnessed properly. When the ten findings are put together, a pattern emerges. Reverse Process Effectiveness is not one of five variables, but is rather the hinge that all the others hang on. Return Information Quality is worth its pound of weight and so are Return Volume Uncertainty and Return Decision Quality, but only if and when they are transformed into something useful during the process. It is that conditional structure that is the true discovery here for warehouses in the FMCG category in Indonesia.

CONCLUSION AND SUGGESTIONS

Conclusion

The empirical evidence obtained in this study supports the following conclusions.

1. Return Volume Uncertainty and Return Decision Quality do not directly drive Warehouse Operational Performance (H1, H3 not supported), while Return Information Quality and Reverse Process Effectiveness do (H2, H4 supported); Reverse Process Effectiveness is the strongest single direct predictor of performance in the model.
2. All three antecedents significantly strengthen Reverse Process Effectiveness (H5, H6, H7 supported). Return Decision Quality has the largest effect, followed by Return Volume Uncertainty and Return Information Quality, indicating that decision-making quality is the most influential lever for building an effective reverse process.
3. Reverse Process Effectiveness fully mediates the effects of Return Volume Uncertainty and Return Decision Quality on performance (H8, H10 supported), while it partially mediates Return Information Quality, which affects performance both directly and through the process (H9 supported).
4. Taken together, these findings position Reverse Process Effectiveness not as one variable among several but as the central mechanism that converts upstream return-handling inputs, information quality, decision quality, and the management of volume uncertainty, into measurable warehouse operational performance gains in Indonesian FMCG companies.

Limitations

Three limitations apply. The study reflects only one phase of the FMCG warehouse operations in Indonesia; therefore, the conclusions drawn should not be interpreted as valid for other sectors, countries, or time frames at this time. Furthermore, it evaluates only a small number of variables, excluding, for example, digital maturity, organizational culture or top-management support. The cross-sectional design provides a snapshot of what is happening at a given point in time and not a picture of change over time.

Recommendation

Reverse Process Effectiveness should be the No. 1 investment priority because it makes information quality, decision quality, and readiness for volume swings a reality. Return cycles should be accelerated, handling costs reduced and procedures streamlined with definite completion targets. As well as quicker, more consistent decision-making with clear cross-departmental accountability and flexible staffing and storage, accurate documentation and real-time status tracking via an integrated WMS are still important, as Return Information Quality also pays off directly.

Future research can be tested in FMCG other than Indonesia, such as in pharmaceuticals, retail or e-commerce, and Return Volume Uncertainty and Return Decision Quality only functioned as a full mediator. A longitudinal approach combined with interviews could further explore these pathways.

Author Contribution

I handled the research conceptualization, created the theoretical framework, carried out the data collection, data analysis, data interpretation and manuscript writing and revision, and read and approved the manuscript for publication.

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