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EXPLORING THE LINKAGES OF RISK FACTORS IN THE REVERSE LOGISTICS OF DELIVERING FAST-MOVING CONSUMER GOODS: A CASE STUDY AT PT X

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ABSTRACT

The Fast-Moving Consumer Goods (FMCG) industry faces complex challenges in managing product returns within its reverse logistics process. This study aims to identify and analyze the interrelationships among risk factors influencing the return process in a logistics service company that supports FMCG distribution. Using the **Decision-Making Trial and Evaluation Laboratory (DEMATEL)** method, data were collected from three logistics experts to evaluate the causal relationships among identified risk factors across five business processes: warehousing, transportation, quality, order processing, and customer-related issues. The analysis revealed that **master data issues (C2)** are the strongest causal factor influencing other variables, acting as a critical driver for systemic change. **Poor inventory accuracy (B1)** emerged as the most prominent and central factor within the network, functioning as both a cause and mediator of multiple interactions. Conversely, **delivery delays (B6)** and **incomplete products (B8)** were identified as the most affected factors, serving as indicators of overall system performance. The findings highlight that improving data management and inventory accuracy can significantly enhance the efficiency and sustainability of reverse logistics in FMCG operations. This research contributes to the understanding of systemic risk linkages in reverse logistics and provides a foundation for strategic decision-making in sustainable supply chain management.

Keywords: *Reverse Logistics, FMCG, Risk Factors, DEMATEL, Supply Chain Sustainability*

INTRODUCTION

The Fast-Moving Consumer Goods (FMCG) industry plays an important role in both national and global economies. Products in this industry, such as food, beverages, and household necessities, have short life cycles and very fast turnover. With such characteristics, FMCG supply chain management often faces greater challenges compared to other industries, especially in terms of the product return (reverse logistics) process. Product returns within the supply chain can occur for various reasons, such as production defects, errors or mismatches in the distribution process, or customer return policies. However, if not properly managed, product returns can result in increased logistics costs, financial losses, and environmental impacts due to product waste.

PT Log1 is one of the logistics service providers currently collaborating with PT FMCG1 in storing and delivering FMCG goods to customers. The current issue is frequent complaints in product delivery to PT FMCG1 customers, particularly in the transportation department. This is due to damaged goods, which subsequently results in a product return process. Interviews with PT Log1's transportation manager revealed that the return process is influenced by various factors, such as 1) damaged products upon receipt by the customer, and 2) price differences, where the shipping price at the time of delivery has not been updated. This will certainly have a significant impact on the sustainability of PT Log1's collaboration with FMCG companies and the associated transporters. In the context of a sustainable supply chain (SSC), the product returns process is playing an increasingly crucial role. SSC integrates economic, social, and environmental dimensions to ensure that business practices are not only profitable but also environmentally friendly and socially responsible. However, the risks involved in the product returns process are more complex than those in the forward logistics distribution. From the perspective of a logistics service company, several major challenges exist in the FMCG product returns process, including: (1) uncertainty in return volumes, which results in difficulties with logistics planning. (2) lack of an efficient reverse logistics infrastructure, thus slowing down the product return process. (3) high costs in managing returned products, especially if the product requires inspection or repair before it can be resold.

Several studies have shown that the Decision-Making and Trial Evaluation Laboratory (DEMATEL) approach can be used to map and analyze the interrelationships between risk factors in the supply chain, particularly in handling product returns. By using this method, decision-makers can understand the causal relationships between risk factors, thereby designing more effective mitigation strategies. Previous research by Agnestia & Yuliawati (2019) described the existing obstacles affecting the fulfillment of lead time in a manufacturing context. This research does not involve an analysis in the context of product returns or logistics services in the FMCG industry. Giannakis & Papadopoulos (2021) explain reverse logistics in the FMCG industry using DEMATEL combined with Fuzzy ANP to identify risk factors associated with the management of returned products, particularly in economic and environmental contexts.. This study focuses on economic and environmental factors in product return management. (Yuliawati & Brilliana, 2022), in their study titled "Linkages Analysis Risk Factors of the Return Process in Logistics Fast-Moving Consumer Goods," used the DEMATEL method, where the risk of product returns due to near-expiration, ordering errors, and damaged stock affects the sustainable supply chain in the FMCG industry. The results of their study explain the analysis of the linkages of risk factors in the product return process by identifying 22 risk factors that cause the product return process, which are grouped into 4 business processes, namely warehousing, transportation/distribution, production/supply, and order processing. The results of this study serve as a reference for decision-makers to prioritize risk factor management that is related to other risk factors, because the impact will be maximized. The difference between this study and previous studies lies in the object of study. This study focuses on a logistics service company, identifying five business processes at PT Log1: warehousing, transportation, quality, order processing, and customer issues. In addition, the difference from previous research is in the assessment indicators used, where this research develops the research indicators of (Yuliawati & Brilliana, 2022) and takes into account customer feedback.

This study aims to identify and analyze the key risk factors in the FMCG product returns process at a sustainable logistics service company. With a deeper understanding of these risk factors, the company can optimize its returns and improve logistics efficiency, while supporting long-term business sustainability. The research problem proposed in this study is how to identify the main risk factors in the product return process in the sustainable FMCG industry, particularly from a logistics service perspective. The purpose of this study is to identify and analyze the main risk factors in the product return process in the sustainable FMCG industry, particularly from a logistics service perspective.

METHODOLOGY

The DEMATEL (Decision-Making Trial and Evaluation Laboratory) method was first introduced at Battelle Memorial Institute in the late 1970s. It was designed to analyze and solve complex decision-making problems by presenting relationships among factors in a structured manner. Specifically, DEMATEL separates groups of causes from groups of effects. This allows for the identification of causal chains within a system.

According to Si et. al., the input to the DEMATEL method is a matrix called a direct relation matrix. (*direct-relation matrix*). The following Z matrix is an example of a direct relation matrix involving n factors F_1, F_2, ..., F_n.

$$Z = \begin{bmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & \ddots & \vdots \\ z_{n1} & \cdots & z_{nn} \end{bmatrix}$$

The rows in the Z matrix represent the influencing factors, while the columns represent the factors that are influenced. The following are the requirements for the Z value. z_{ij}.

1. z_{ij} is equal to 0, 1, 2, 3, or 4 for every $i, j = 1, 2, 3, ..., n$
2. $z_{ij} = 0$ means "factor *i* has no influence at all on factor *j*", $z_{ij} = 1$ means "factor *i* has little influence on factor *j*", $z_{ij} = 2$ means "factor i has a moderate level influence on factor j", $z_{ij} = 3$ means "factor i has a strong influence on factor j", $z_{ij} = 4$ means "factor i has a very strong influence on factor j"
3. $z_{ii} = 0$ for $i = 1, 2, 3, ..., n$
4. In the case that there is more than one experts who do the assessments, z_{ij} is the arithmetic mean of the values assigned by the experts. Suppose l experts are involved in the assessment, and the k^th^ expert assigns a value $z_{ij}^{(k)}$ for the strength of the influence of factor *i* on factor *j*. As a result, $z_{ij} = \frac{1}{l}\sum_{k=1}^{l} z_{ij}^{(k)}$.

In addition to direct influences, the Dematel method takes into account indirect influences or interactions between factors. The magnitude of the total influence of factors on other factors can be seen from the total influence matrix obtained from the sum of an infinite series of powers of the direct-relation matrix. For the series to converge, the eigenvalues of the direct-relation matrix must be less than 1. Therefore, the direct-relation matrix must first be normalized so that the total influence matrix can be constructed. The normal matrix is as follows.

$$X = \frac{Z}{s}$$

Here, $s = \max\left(\max_{1\le i\le n} \sum_{j=1}^{n} z_{ij}, \max_{1\le i\le n} \sum_{i=1}^{n} z_{ij}\right)$.

Using X, the total influence matrix T is obtained by adding up the direct impacts and all indirect impacts as follows.

$T = X + X^2 + X^3 + \cdots + X^h = X(I - X)^{-1}$ for $h \to \infty$.

By adding the rows and columns, two vectors will be obtained, namely the row sum (R) and the column sum (C). These vectors can be expressed as follows.

$R = [r_i]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1}$

$C = [c_j]_{n\times 1} = \left[\sum_{i=1}^{n} t_{ij}\right]'_{1\times n}$

In the vector R, each r_i represents the sum of the direct and indirect influences that factor F_i exerts on other factors. In the vector C, each c_j represents the sum of the direct and indirect impacts that factor F_j receives from other factors. The vector (R+C) is hereinafter called prominence and measures the degree/level of central role that factors have in the system. The higher the prominence of a factor, the more important its role in the system. The vector (R-C) is called the relation and measures the net effect of factors in the system. If $r_j - c_j > 0$, it is concluded that factor F_j has a net influence on other factors and is classified as a cause. Conversely, if $r_j - c_j < 0$, it is concluded that factor F_j is influenced by other factors as a whole and must be classified as an effect. From these prominence and relation vectors, an influential relation map (IRM) can be created. The IRM contains two axes. The horizontal axis represents prominence, and the vertical axis represents relations. Each factor has a pair of coordinates; the first coordinate is R + C, and the second coordinate is R - C. Thus, each factor has a location on the IRM plane.

RESULTS AND DISCUSSION

1. Identifying the problem and related factors. At this stage, the researcher determines the problem to be solved using DEMATEL along with the important factors related to the problem.
2. Developing the questionnaire. The researcher designed the questionnaire in the form of a pair-by-pair comparison of the factors obtained in the previous step.
3. Collecting data. The researcher distributed the questionnaire to three experts in their respective fields to complete the questionnaire.

4. Processing data. In processing the data, the researcher implemented the steps as described by Si et. al., in the following order: a) constructing the direct relationship matrix Z, b) determining the normalized direct influence matrix X, c) developing the total influence matrix T, d) creating an influential relationship map (IRM).
5. Visualizing the data processing output. The author created a cause-and-effect diagram/influence diagram that illustrates the relationships between factors.
6. Interpreting and analyzing data processing output. The author identified groups of causes and groups of effects based on the prominence and relation values obtained during the data processing stage. Next, the researchers analyzed the causal relationships between the factors.

Based on the responses from the three experts, we have the following direct-relationship matrix *Z*.

Table 1

The Direct-Relation Matrix Z

	A1	A2	A3	A4	B1	B2	B3	B4	B5	B6	B7	B8	B9	C1	C2	C3
A1	0.000	0.000	0.000	1.667	2.333	3.000	0.667	0.000	1.333	0.667	0.667	1.333	0.333	0.333	0.000	0.000
A2	0.000	0.000	1.000	0.667	0.000	0.333	0.000	4.000	4.000	3.333	0.000	0.000	0.000	0.000	0.000	0.000
A3	0.000	2.333	0.000	0.000	0.000	0.333	0.000	3.667	3.667	3.667	0.000	0.000	0.000	0.000	0.000	0.000
A4	1.333	0.000	0.000	0.000	3.667	2.667	1.667	0.000	0.000	0.667	0.000	0.333	1.000	0.333	0.000	0.000
B1	2.333	0.000	0.000	2.333	0.000	2.000	3.333	0.000	0.000	1.000	0.000	3.000	2.667	1.333	0.333	0.667
B2	1.333	0.000	0.000	1.667	2.000	0.000	1.667	0.000	3.000	1.000	1.333	2.333	1.000	0.000	0.000	0.000
B3	1.000	0.000	0.000	2.000	2.667	0.333	0.000	0.000	0.000	1.333	0.000	3.667	2.333	1.333	0.333	1.667
B4	0.000	4.000	2.667	0.667	0.000	0.333	0.000	0.000	2.667	4.000	0.000	2.667	0.000	0.333	0.000	0.000
B5	0.333	0.667	0.667	0.000	1.000	0.667	0.000	1.333	0.000	0.667	1.000	1.333	0.000	0.000	0.000	0.000
B6	0.667	0.667	1.000	0.000	0.000	0.000	0.000	1.333	0.000	0.000	0.000	0.000	0.667	1.000	0.000	0.667
B7	2.000	0.000	0.000	0.000	0.000	2.000	0.333	0.333	4.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B8	0.333	0.000	0.000	0.000	0.000	0.333	2.667	0.667	0.000	0.000	0.000	0.000	3.000	2.333	0.000	1.667
B9	0.333	0.000	0.000	1.667	1.667	0.000	1.333	0.000	0.000	1.333	0.000	2.000	0.000	2.333	0.333	1.667
C1	0.333	0.000	0.000	0.333	0.333	0.000	1.000	0.000	0.000	0.333	0.000	1.000	2.667	0.000	0.333	2.333
C2	0.667	0.000	0.000	0.000	1.000	0.000	2.000	0.000	0.000	0.000	0.000	1.000	2.333	4.000	0.000	1.000
C3	0.000	0.000	0.000	0.000	0.000	0.000	0.667	0.000	0.000	0.000	0.000	1.000	1.000	2.667	0.333	0.000

The normalized direct influence matrix *X* is as follows.

Table 2

Normalized Direct Influence Matrix *X*

	A1	A2	A3	A4	B1	B2	B3	B4	B5	B6	B7	B8	B9	C1	C2	C3
A1	0.000	0.000	0.000	0.085	0.119	0.153	0.034	0.000	0.068	0.034	0.034	0.068	0.017	0.017	0.000	0.000
A2	0.000	0.000	0.051	0.034	0.000	0.017	0.000	0.203	0.203	0.169	0.000	0.000	0.000	0.000	0.000	0.000
A3	0.000	0.119	0.000	0.000	0.000	0.017	0.000	0.186	0.186	0.186	0.000	0.000	0.000	0.000	0.000	0.000
A4	0.068	0.000	0.000	0.000	0.186	0.136	0.085	0.000	0.000	0.034	0.000	0.017	0.051	0.017	0.000	0.000
B1	0.119	0.000	0.000	0.119	0.000	0.102	0.169	0.000	0.000	0.051	0.000	0.153	0.136	0.068	0.017	0.034
B2	0.068	0.000	0.000	0.085	0.102	0.000	0.085	0.000	0.153	0.051	0.068	0.119	0.051	0.000	0.000	0.000
B3	0.051	0.000	0.000	0.102	0.136	0.017	0.000	0.000	0.000	0.068	0.000	0.186	0.119	0.068	0.017	0.085
B4	0.000	0.203	0.136	0.034	0.000	0.017	0.000	0.000	0.136	0.203	0.000	0.136	0.000	0.017	0.000	0.000
B5	0.017	0.034	0.034	0.000	0.051	0.034	0.000	0.068	0.000	0.034	0.051	0.068	0.000	0.000	0.000	0.000
B6	0.034	0.034	0.051	0.000	0.000	0.000	0.000	0.068	0.000	0.000	0.000	0.000	0.034	0.051	0.000	0.034
B7	0.102	0.000	0.000	0.000	0.000	0.102	0.017	0.017	0.203	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B8	0.017	0.000	0.000	0.000	0.000	0.017	0.136	0.034	0.000	0.000	0.000	0.000	0.153	0.119	0.000	0.085
B9	0.017	0.000	0.000	0.085	0.085	0.000	0.068	0.000	0.000	0.068	0.000	0.102	0.000	0.119	0.017	0.085
C1	0.017	0.000	0.000	0.017	0.017	0.000	0.051	0.000	0.000	0.017	0.000	0.051	0.136	0.000	0.017	0.119
C2	0.034	0.000	0.000	0.000	0.051	0.000	0.102	0.000	0.000	0.000	0.000	0.051	0.119	0.203	0.000	0.051
C3	0.000	0.000	0.000	0.000	0.000	0.000	0.034	0.000	0.000	0.000	0.000	0.051	0.051	0.136	0.017	0.000

By applying the formulas above, the total influence matrix *T* is as follows.

Table 3
Total Influence Matrix *T*

	A1	A2	A3	A4	B1	B2	B3	B4	B5	B6	B7	B8	B9	C1	C2	C3
A1	0.081	0.016	0.014	0.169	0.225	0.228	0.155	0.030	0.130	0.103	0.059	0.203	0.141	0.105	0.012	0.066
A2	0.038	0.093	0.120	0.071	0.050	0.060	0.042	0.288	0.300	0.293	0.021	0.096	0.053	0.051	0.004	0.034
A3	0.034	0.207	0.076	0.038	0.042	0.056	0.036	0.288	0.297	0.318	0.020	0.091	0.049	0.049	0.004	0.033
A4	0.151	0.011	0.011	0.107	0.297	0.215	0.215	0.022	0.055	0.108	0.022	0.176	0.188	0.119	0.015	0.078
B1	0.211	0.015	0.015	0.241	0.172	0.201	0.333	0.032	0.060	0.148	0.024	0.346	0.326	0.227	0.038	0.159
B2	0.149	0.022	0.021	0.172	0.219	0.094	0.209	0.042	0.209	0.130	0.090	0.264	0.187	0.109	0.014	0.081
B3	0.131	0.014	0.013	0.197	0.252	0.101	0.159	0.029	0.036	0.143	0.013	0.337	0.289	0.216	0.036	0.192
B4	0.046	0.276	0.196	0.081	0.059	0.067	0.068	0.142	0.265	0.347	0.020	0.224	0.087	0.094	0.006	0.057
B5	0.052	0.069	0.060	0.038	0.088	0.072	0.053	0.110	0.067	0.101	0.061	0.133	0.057	0.046	0.005	0.033
B6	0.049	0.068	0.073	0.025	0.026	0.021	0.028	0.104	0.049	0.061	0.006	0.047	0.068	0.083	0.004	0.059
B7	0.139	0.023	0.019	0.047	0.068	0.152	0.069	0.049	0.257	0.052	0.028	0.084	0.051	0.036	0.004	0.026
B8	0.059	0.014	0.011	0.068	0.081	0.052	0.213	0.049	0.025	0.062	0.007	0.118	0.255	0.215	0.016	0.166
B9	0.076	0.010	0.010	0.150	0.169	0.058	0.175	0.021	0.022	0.121	0.008	0.214	0.135	0.223	0.032	0.167
C1	0.049	0.005	0.005	0.065	0.075	0.029	0.119	0.011	0.012	0.054	0.004	0.131	0.211	0.088	0.028	0.174
C2	0.084	0.006	0.005	0.074	0.134	0.044	0.200	0.013	0.018	0.055	0.007	0.173	0.247	0.305	0.018	0.147
C3	0.019	0.002	0.002	0.028	0.034	0.014	0.079	0.006	0.006	0.022	0.002	0.100	0.113	0.182	0.025	0.050

The total influence matrix displays the overall magnitude of each factor's influence on every other factor, considering both direct and indirect relationships. The matrix displays a large number of positive values, indicating a high degree of interrelationship between the factors. The system is complex, with numerous interactions. Some factors have stronger relationships with one factor but less so with others. This is evident in the diversity of values within the matrix.

Table 4
Prominence and *Relation* of the Factors

CODE	FACTOR	R	C	R+C	R-C	DESCRIPTION
B1	Poor Inventory Accuracy	2.546	1.991	4.537	0.555	cause
B3	Wrong product stuffing	2.157	2.152	4.310	0.005	cause
B8	Incomplete product	1.411	2.738	4.149	-1.327	effect
B9	Error in order execution	1.593	2.456	4.049	-0.863	effect
B2	Poor Product Handling	2.013	1.465	3.477	0.548	cause
A4	Full Storage	1.790	1.570	3.360	0.220	cause

B4	Accident during delivery	2.034	1.236	3.270	0.797	cause
C1	Error in order management	1.061	2.148	3.209	-1.087	effect
A1	Poor storage handling	1.736	1.369	3.105	0.367	cause
B6	Delay in delivery	0.771	2.118	2.889	-1.347	effect
B5	Damage during delivery	1.043	1.807	2.850	-0.764	effect
A2	Poor truck condition	1.612	0.852	2.464	0.761	cause
A3	Poor road infrastructure	1.638	0.651	2.289	0.987	cause
C3	Customer system error	0.684	1.521	2.205	-0.838	effect
C2	Master data issue	1.529	0.259	1.788	1.270	cause
B7	Poor packaging quality	1.105	0.390	1.495	0.715	cause

Based on the *prominence and relation* values of these factors, the following influential relation map is obtained.

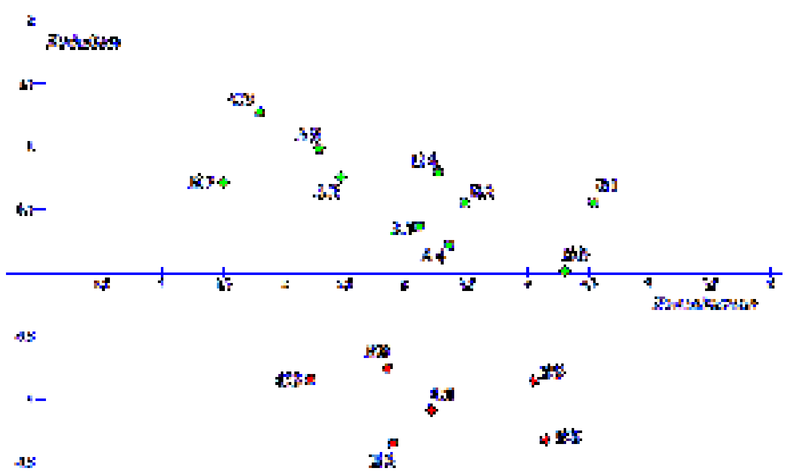

Figure 1

The Influential Relation Map (*IRM*)

From the figure above, it appears that factor C2 (*master data issue*) occupies the highest position. This factor has the highest *relationship* value. The very high positive D-R value (1.270) indicates that C2 is the strongest causal factor in the system. This factor has the most significant net influence on other factors. Its high causal influence makes it a strategically important factor. If the goal is to influence system outcomes, focusing on C2 is likely to be highly effective. From this, it can be concluded that changes or interventions related to C2 are likely to have a substantial and broad impact on system behavior. Factor C2 acts as a strong "initiator" or "driver" that moves the system. On the other hand, a very low *prominence* value (1,788) indicates that C2 has a fairly low overall importance in the system. This factor is not a factor that is heavily influenced by other factors. So, although C2 heavily influences the system, C2 itself is not heavily influenced by the system.

The second extreme point after C2 is B1 (*poor inventory accuracy*), the rightmost point in the IRM. Factor B1 has the highest *prominence* value, indicating that it is the most prominent factor in the system. This means that it plays a central and critical role, influencing and being influenced by many other factors. B1 is the (*central hub*) of the network. On the other hand, the positive *relation* value (0.555) indicates that B1 is classified as a cause. From the fact that B1 is the center of the network and classified as a cause, it can be concluded that B1 sends and receives significant influence, making it a key connector and mediator. The strategic impact is that the changes or interventions related to B1 will have a broad impact on the system.

Factor B6 (*delay on delivery*) has the lowest relationship value, indicating that it is the most influenced factor in the system. This factor is the primary impact or outcome of the system and, in turn, the primary indicator of overall system performance. Similarly, factor B8 (*incomplete product*) also has a *relationship* value quite close to B6. Therefore, this factor is also the primary impact or outcome of system interaction and is an important indicator of overall system performance. Observing these factors can provide insight into the effectiveness of interventions or changes made to the system. Furthermore, both B6 and B8 are highly vulnerable to changes in other factors. Any change in causal factors, such as *master data issues* (C2) and *poor inventory accuracy* (B1), will significantly impact the *delay in delivery* (B6) and incomplete product (B8). The very low relationship values of C2 and B1 make them particularly vulnerable factors. Given their vulnerability, B6 and B8 must be closely monitored to track the impact of any changes or interventions.

The other extreme is B7 (*poor packaging quality*), which has the lowest prominence value, indicating that B7 has the lowest overall importance or prominence in the system. A positive relationship value (0.715) indicates that B7 is classified as a causal factor, meaning it has a net effect on the other factors. Despite its low prominence, it still contributes to driving the system's behavior. The combination of low prominence and a positive relationship value shows that B7 has a specific or directed influence on a small number of factors, rather than a broad and widespread influence.

CONCLUSION

The master data issue stands out as the strongest causal factor. It acts as a powerful initiator of change, making it a critical point for strategic interventions aimed at fundamental system change. *Poor inventory accuracy* is the most prominent factor, serving as a hub in the network that connects and influences many other factors. It is both a cause and a recipient of influence, making it a key mediator and a primary target for interventions aimed at widespread, network-wide change. Manipulation of the *master data issue* can initiate fundamental change, while manipulation of *inventory accuracy* can achieve widespread change throughout the network. The *Delay in delivery* and incomplete product are the most influenced factors, representing the primary outcomes or effects of system dynamics. These two factors are highly susceptible to change and serve as key indicators of system performance. They should be monitored as primary outputs. *Poor packaging quality* has the lowest *prominence,* but still deserves attention because it still exerts a causal influence.

REFERENCES

Wu, W. W., Lan, L. W., & Lee, Y. T. (2011). Exploring decisive factors affecting an organization's SaaS adoption: A case study. *International Journal of Information Management*, *31*(6), 556–563. https://doi.org/10.1016/j.ijinfomgt.2011.02.007

Yuliawati, E., & Brilliana, C. W. (2022). Linkages analysis risk factors of the return process in logistics fast moving consumer goods. *Jurnal Sistem Dan Manajemen Industri*, *6*(2), 198–110. https://doi.org/10.30656/jsmi.v6i2.4736

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(Wu et al., 2011)