

Article

Causal Analysis of Reverse Logistics Determinants for Sustainable E-Commerce Supply Chains

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Abstract

The continued growth of e-commerce has changed the role of reverse logistics, turning it from a supporting activity into an important element of sustainable and resilient supply chain management. Handling product returns efficiently requires a clear understanding of how different logistics factors influence one another within the broader system. This study examines and models the causal links among six major factors through the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method. Using evaluations provided by a panel of domain experts, the analysis measures the strength of interactions between the selected variables and identifies those that act as driving forces as well as those that mainly respond to influences from other factors. The resulting model offers a practical basis for decision-making by showing which factors generate the strongest effects across the reverse logistics network. This perspective helps managers direct available resources toward the elements capable of producing the greatest influence on overall system performance. As a result, organizations can improve the use of resources while supporting both operational efficiency and environmental objectives throughout the supply chain. By applying a causal analysis framework, this research delivers a useful instrument for understanding return management processes in e-commerce. The findings support more informed strategic decisions and provide guidance for companies seeking to improve sustainability performance within a market environment shaped by circular economy principles and frequent change.

Keywords: returns management; DEMATEL; multi-criteria decision-making (MCDM); cause-and-effect relationships; circular economy; logistics optimization; managerial support; resource efficiency; environmental outcomes



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1. Introduction

The rapid growth of e-commerce has brought major changes to supply chain operations, extending managerial attention beyond product delivery to include the handling of returned goods [1]. Within this environment, returns management has become an important part of business strategy rather than a peripheral operational activity. The increasing volume of returned products has made reverse logistics essential for preserving customer confidence and supporting sustainability objectives associated with the circular economy [2,3]. At the same time, inefficient return processes continue to generate considerable difficulties for organizations. These difficulties include elevated operating expenses, excessive resource consumption, higher energy use, and growing environmental pressures caused by increasing waste generation and carbon emissions [4,5]. For this reason, adopting sustainable reverse logistics practices has become a business requirement for firms seeking long-term stability and stronger environmental performance while responding to regulatory demands and changing customer expectations regarding responsible corporate behaviour [6,7].

Managing reverse logistics successfully depends on several interconnected elements that extend far beyond the physical collection of returned products [8]. Transport planning, digital solutions, return policy design, and sustained managerial involvement must operate together in a coordinated manner [9,10]. Although each factor contributes to system performance, the final outcome depends largely on the way these elements influence one another [11]. For example, efficient transportation planning cannot deliver the expected benefits if return processing activities are poorly organized. Likewise, technological investments may produce limited results when managerial support is weak or inconsistent [12,13]. Understanding these relationships is necessary for organizations aiming to replace reactive decision-making with a proactive and evidence-based approach to returns management [14].

Previous studies have examined numerous variables associated with sustainability in logistics. However, much of the existing research discusses these variables separately and pays less attention to the causal links that connect them [15]. This limitation is important because managers often operate under resource constraints and require more than a simple inventory of relevant factors when making strategic decisions [16]. Improving sustainability performance requires a clearer understanding of which variables generate influence across the system and which mainly reflect the consequences of changes initiated elsewhere. Identifying these relationships supports better prioritization and strengthens the basis for informed managerial action [17].

Investigating such interconnected factors requires an appropriate Multi-Criteria Decision-Making (MCDM) approach. Techniques including the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), and Interpretive Structural Modeling (ISM) are widely applied in studies examining relationships among variables. Nevertheless, these methods may face difficulties when representing asymmetric influences and developing a transparent cause-and-effect structure without predefined hierarchical arrangements [18]. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method provides a suitable alternative because it measures the strength of interrelationships and determines how strongly each factor influences the others. Through this process, variables can be classified according to their causal role within the system. The resulting relational map helps identify the points where managerial intervention is most likely to generate meaningful system-wide improvements [19].

Against this background, the present study applies the DEMATEL method to the context of product returns in e-commerce. The approach enables the visualization and assessment of causal relationships within a complex logistics environment and helps

identify the factors that exert the strongest influence on overall supply chain outcomes. The primary objective is to examine the interdependencies among six factors considered important for sustainable reverse logistics practices in e-commerce. In doing so, the research extends existing knowledge by moving from simple factor identification toward a structured analysis of causal priorities. The findings offer a clearer view of the influence hierarchy among the selected variables and support more effective managerial decisions aimed at improving sustainability and operational performance in a rapidly changing digital marketplace.

2. Theoretical Framework

This section presents the conceptual basis of the selected variables by linking them to established theories and previous studies in logistics, sustainability, and management. The six factors examined in this research were identified through a detailed review of the relevant literature. The selection process focused on variables that are repeatedly recognized as important for understanding reverse logistics activities in the e-commerce environment.

Transport routes (F_1) represent a key element of logistics performance because they directly influence operating expenses and environmental outcomes [4,20,21]. Within reverse logistics systems, route planning for returned products is generally more difficult than traditional product distribution [5]. This complexity arises from uncertainty related to collection locations, pickup schedules, and fluctuating return volumes [22]. Poor route planning may increase energy use, extend processing times, and weaken relationships with both customers and business partners [23]. As a result, examining the connections between F_1 and the other system components is important for identifying improvements that support emission reduction objectives and more sustainable logistics operations [24].

The performance of reverse logistics activities is strongly influenced by an organization's ability to handle returned products efficiently once they arrive at distribution facilities [12]. For this reason, returns processing systems (F_2) occupy an important position within the logistics structure [25]. Modern sorting, inspection, repair, and refurbishment technologies, frequently supported by automation and Artificial Intelligence, can shorten processing cycles and reduce operational costs while improving product value recovery [2,3]. Weak processing capabilities often result in inventory accumulation, slower reimbursement procedures, and higher waste generation, creating both economic and environmental consequences [6,26]. Previous studies indicate that advanced technological solutions within processing facilities contribute significantly to logistics effectiveness and operational performance [27,28].

Customer interaction also plays an important role in the returns process [9]. Digital customer technologies (F_3), including online return portals, mobile applications, and real-time tracking tools, make the return experience easier and more transparent for consumers [11]. When supported by digital solutions, return procedures become easier to understand and manage, reducing the burden on customer service departments while strengthening customer loyalty [29,30]. From a broader system perspective, these technologies improve information exchange throughout the return journey and reduce uncertainty at every stage of the process [3,31].

Effective materials management (F_4) contributes directly to waste reduction and supports circular economy objectives [6]. This factor includes practices such as the use of reusable or environmentally friendly packaging, recycling activities, and the refurbishment or reuse of returned products [32]. Organizations that actively invest in these practices can reduce environmental pressures while improving resource utilization [7]. Furthermore, packaging choices made during the returns process can simplify recovery activities and support better environmental outcomes [33].

Top management commitment (F_5) is widely recognized as a determining factor in the success of sustainability-related initiatives [10]. Reverse logistics programs often require substantial investments and long-term organizational support. In the absence of managerial commitment, these initiatives may receive insufficient resources or lose priority when short-term financial concerns dominate decision-making processes [16]. Leadership plays an important role in establishing organizational values, allocating resources, and translating sustainability objectives into operational actions [13]. Consequently, the degree of managerial involvement has a direct influence on the implementation of sustainable business practices and long-term organizational transformation [14,34].

Return policies (F_6) provide the formal structure through which return activities are managed and communicated to consumers [1]. Policies that are clear, flexible, and easy to understand can lower the frequency of unnecessary returns while improving customer satisfaction [35]. In contrast, return procedures perceived as restrictive or confusing may damage customer perceptions and reduce purchase intentions [36]. Their importance extends beyond operational management because they also influence consumer decision-making before a purchase takes place, contributing to a more predictable and stable e-commerce environment [37,38].

The selection of the six factors was based on a review of the relevant literature on reverse logistics in e-commerce. During this process, we found that previous studies examine a wide range of variables because they focus on different industries, research objectives, and operational settings. As a result, the literature contains a large number of factors that vary considerably from one study to another. For this reason, our objective was to identify the factors that appear most frequently across previous studies and are applicable to product return processes in e-commerce. The preliminary list was further discussed with the experts involved in this research, who confirmed that these six factors are among the most relevant for evaluating the efficiency of reverse logistics activities. Another reason for limiting the number of factors is related to the DEMATEL method itself. If the number of factors is denoted by n , the number of pairwise influence assessments that each expert must complete is $n^2 - n$. This number increases rapidly as additional factors are included, leading to a much longer questionnaire and a greater risk of respondent fatigue. For this reason, DEMATEL studies commonly focus on a limited number of factors, often between four and six, in order to keep the evaluation process manageable and to obtain consistent expert judgments.

Examining these six factors together provides a clearer understanding of the mechanisms that shape sustainable reverse logistics practices. Although each variable has its own importance, none operate independently. The interactions among them create a network of influences that determines overall system performance. Understanding these relationships is necessary for identifying the factors that generate the strongest effects across the logistics structure. The following section describes the methodology used to analyse these interactions and establish the causal structure of the selected factors.

3. Methodology

This research employs a mixed-method design based on the DEMATEL approach, combining qualitative expert judgment with quantitative data analysis. The qualitative component relies on the expertise of professionals with substantial experience in logistics and return management, while the quantitative component is represented by the mathematical processing of the collected evaluations. This combination allows the analytical model to reflect practical industry knowledge and supports the credibility of the findings.

Reverse logistics represents one of the operational mechanisms through which Circular Economy principles are implemented. However, the transition from a linear to a

circular supply chain does not depend on isolated improvements within individual logistics activities. Product recovery, reuse, refurbishment, and recycling require continuous coordination among transport planning, materials management, return processing systems, digital technologies, organizational support, and return policies. These activities form an interconnected operational system in which decisions taken in one area influence the performance of several others. Consequently, understanding reverse logistics requires moving beyond the analysis of individual determinants toward the examination of their causal relationships.

From this perspective, the DEMATEL approach provides more than a ranking of important factors. It enables the identification of causal interactions that explain how operational and managerial decisions propagate throughout the reverse logistics system. This systemic interpretation is consistent with Circular Economy principles, which emphasize that value recovery depends on the coordination of multiple activities rather than on improvements in isolated processes. Therefore, the objective of this study is not only to identify the most relevant reverse logistics factors, but also to explain how they influence one another within the operational structure of sustainable e-commerce supply chains.

The participant selection process focused on professionals holding managerial positions within logistics and operations departments of logistics centres operating in Romania. To be included in the study, participants were required to have a minimum of five years of experience in supply chain activities, with direct involvement in reverse logistics and return flow management. This requirement was established because experienced managers are generally better positioned to recognize risks that occur infrequently but may produce significant consequences for logistics performance. The emphasis on managerial roles was intended to obtain a strategic perspective on the contribution of reverse logistics to long-term sustainability objectives.

The DEMATEL technique was selected because of its ability to analyse complex relationships among factors and its suitability for studies involving relatively small groups of highly qualified experts. Following recommendations from previous methodological studies [18,39], the evaluation was conducted with a panel consisting of six specialists. Within the DEMATEL framework, the value of expert knowledge is considered more important than the size of the sample itself. The selected experts offered insights grounded in practical experience, making the resulting model more representative of actual logistics operations. Concentrating on Romanian logistics centres also provides a clearer understanding of how local business conditions and infrastructure shape reverse logistics practices in the e-commerce sector.

Data collection was carried out between December 2025 and January 2026. The research instrument consisted of a direct relationship matrix containing the six factors included in the analysis. Participants evaluated the degree of influence between each pair of factors, generating a total of 36 individual assessments. The evaluations were recorded using a five-point scale:

- 0 = no influence;
- 1 = weak influence;
- 2 = moderate influence;
- 3 = strong influence;
- 4 = very strong influence.

The scores provided by the experts represented the primary input for the DEMATEL analysis, which was used to identify and quantify the causal relationships among the selected variables.

The expert panel consisted of six specialists with more than five years of professional experience in reverse logistics. This minimum experience threshold was established to

ensure that each participant had been exposed to a broad range of operational situations, including both routine and less frequent return management scenarios, allowing them to provide informed judgments regarding the relationships among the selected factors. The experts were selected based on their direct involvement in reverse logistics activities within the e-commerce sector. Following the literature review and the discussions used to define the final set of factors, all experts participated in a briefing session before completing the questionnaire. During this session, the purpose of the study, the meaning of each factor, the DEMATEL evaluation scale, and the procedure for assessing pairwise relationships were explained using the same instructions for all participants. This step was intended to ensure a common understanding of the evaluation criteria and to reduce inconsistencies that could arise from different interpretations of the questionnaire.

The computational procedure followed five consecutive stages.

Step 1: Construction of the average direct-influence matrix (A).

During the opening phase of the computational procedure, the average direct-influence matrix, denoted as A , is generated to synthesize the impact scores assigned by each individual participant. This aggregated matrix is composed of elements a_{ij} , which represent the arithmetic mean of the scores provided by the m experts ($m = 6$):

$$a_{ij} = \frac{1}{m} \sum_{p=1}^m x_{ij}^p \quad (1)$$

In this context, x_{ij}^p indicates the level of influence that evaluator p attributed to the interaction between factor i and factor j .

Step 2: Derivation of the normalized direct-relation matrix (Y).

The average direct-influence matrix A is then transformed into the normalized direct-relation matrix Y by applying the normalization coefficient k :

$$Y = A \cdot k \quad (2)$$

The coefficient k scales every value in matrix A so that all elements remain within the interval from 0 to 1. This operation keeps the total influence associated with each factor within the limits required by the DEMATEL procedure and allows the following matrix calculations to be performed correctly. The normalization stage also contributes to obtaining consistent results because it places all expert evaluations on the same scale before the total influence matrix is derived. As a result, the calculated relationships reflect the common assessment of the expert panel in a stable manner.

The normalization coefficient k is obtained as the reciprocal of the largest row sum in the initial direct-relation matrix A , according to the following expression:

$$k = \frac{1}{\max_{1 \leq i \leq n} \sum_{j=1}^n a_{ij}} \quad (i, j = 1, 2, \dots, n) \quad (3)$$

This normalization procedure is a standard stage of the DEMATEL method because it prepares the matrix for the matrix operations performed in the following steps. After the number of variables n has been established, with $n = 6$ in this study, and matrix Y has been obtained, the total influence matrix T can be calculated.

Step 3: Calculation of the total influence matrix (T).

The total influence matrix combines the direct relationships between factors with the indirect influences transmitted through the entire system.

The first operation consists of calculating the inverse of the difference between the identity matrix I and the normalized matrix Y :

$$M_{INV} = (I - Y)^{-1} \quad (4)$$

In this expression, I denotes the identity matrix, while the difference $(I - Y)$ represents the remaining influence structure after normalization. Computing its inverse makes it possible to account for influence paths that pass through several factors before reaching their destination. This operation incorporates the indirect effects that appear throughout the system.

The total influence matrix T is then obtained by multiplying the normalized matrix by the inverse matrix:

$$T = Y \cdot (I - Y)^{-1} \quad (5)$$

The resulting matrix T includes both direct and indirect effects among all factors. Each element t_{ij} expresses the overall influence that factor i exerts on factor j , providing a complete description of the relationships within the analysed system.

Step 4: Establishment of the significance threshold (α).

After matrix T has been calculated, the significance threshold α is determined. This value is used to distinguish the relationships that are considered important from those with a lower level of influence.

In this study, α was calculated as the arithmetic mean of all elements contained in the total influence matrix T . This approach is frequently applied in DEMATEL studies because it provides an objective reference value for selecting the relationships included in the causal diagram. Every element of matrix T that exceeds α is treated as a significant connection between two factors. Relationships with values below the threshold are excluded from the graphical representation in order to simplify the interpretation of the results and reduce the influence of weak interactions.

The threshold is calculated as follows:

$$\alpha = \frac{\sum_{i=1}^n \sum_{j=1}^n [t_{ij}]}{N} \quad (6)$$

where $N = n^2$ represents the total number of possible relationships included in matrix T .

Step 5: Derivation of prominence and relation vectors.

Following the calculation of the T matrix and the α threshold, two important metrics are determined for every factor: the impact score D_i , which measures the cumulative influence factor i exerts on the whole system, and the receptivity score R_j , which indicates the total influence factor j receives from all other parameters.

The impact score D_i for each factor is derived by summing the entries in the corresponding row of the total influence matrix T :

$$D_i = \left[\sum_{j=1}^n t_{ij} \right]_{n \times 1} = [t_i]_{n \times 1} \quad (7)$$

for each factor $i \in \{1, 2, \dots, n\}$.

A high D_i value signifies that factor i has a substantial capacity to drive or affect other components within the system. Concurrently, the causality score R_j is determined by summing the entries in the respective column of matrix T :

$$R_j = \left[\sum_{i=1}^n t_{ij} \right]_{1 \times n} = [t_j]_{n \times 1'} \quad (8)$$

for each factor $j \in \{1, 2, \dots, n\}$.

An elevated R_j index suggests that the factor is highly susceptible to the influences and dynamics of other variables in the network.

These indicators are used to map the factors onto a cause-and-effect diagram. The horizontal axis ($D_i + R_j$), termed “prominence,” indicates the total importance of the factor in the system. The vertical axis ($D_i - R_j$), termed “relation,” classifies the factor: if $(D_i - R_j) > 0$, the factor is a “net cause” (driver); if $(D_i - R_j) < 0$, the factor is a “net effect.”

4. Results

The application of the DEMATEL methodology started with the acquisition of qualitative insights from a specialized panel of experts regarding the relational dynamics of the selected variables. This analytical journey involved several computational iterations, beginning with the aggregation of individual perspectives and culminating in a definitive classification of logistics factors into either primary causal drivers or reactive effect components.

By synthesizing the professional assessments gathered during the data collection phase, the direct-influence matrix (A) was systematically assembled (Table 1). This matrix serves as the empirical foundation of the study, providing a quantified mean representation of the immediate impact each factor exerts on every other variable within the e-commerce reverse logistics network.

Table 1. Direct influence matrix.

Factor	F ₁	F ₂	F ₃	F ₄	F ₅	F ₆
F ₁	0.000	0.800	1.200	1.400	1.000	1.000
F ₂	1.400	0.000	2.600	2.200	1.600	2.000
F ₃	1.400	2.600	0.000	1.400	1.600	2.200
F ₄	0.800	2.400	0.600	0.000	1.000	1.200
F ₅	4.000	3.800	3.200	3.000	0.000	3.800
F ₆	1.400	2.200	3.000	1.400	1.800	0.000

The subsequent phase involved the derivation of the normalized direct-relation matrix (Y) (Table 2). This was achieved by scaling every element of the initial matrix by a normalization constant, k , based on the maximum row sum. This technical procedure is more than a mere mathematical adjustment; it is a prerequisite for ensuring the convergence of the model and ensuring that the subsequent matrix inversion remains mathematically stable. By establishing this standardized scale, the research provides a transparent view of how initial influences are distributed before they propagate through the broader supply chain framework.

Proceeding from the normalized data, the total influence matrix (T) was calculated (Table 3), representing a hallmark of the DEMATEL approach. This matrix is vital because it moves beyond surface-level connections to capture both direct links and complex, indirect downstream consequences that flow through the system. To focus specifically on the most decisive interdependencies, a structural significance threshold α was established at 0.192. This benchmark, derived from the mean value of all entries in the total influence matrix,

serves as a robust filter to isolate significant causal paths. Only relationships that meet or exceed this α value are considered significant, effectively removing “noise” from weaker interactions to clarify the core structural dependencies of the system.

Table 2. Normalised direct relations matrix.

Factor	F ₁	F ₂	F ₃	F ₄	F ₅	F ₆
F ₁	0.000	0.045	0.067	0.079	0.056	0.056
F ₂	0.079	0.000	0.146	0.124	0.090	0.112
F ₃	0.079	0.146	0.000	0.079	0.090	0.124
F ₄	0.045	0.135	0.034	0.000	0.056	0.067
F ₅	0.225	0.213	0.180	0.169	0.000	0.213
F ₆	0.079	0.124	0.169	0.079	0.101	0.000

Table 3. Total influence matrix highlighting (*) factors with significant influence ($\alpha > 0.192$).

Factor	F ₁	F ₂	F ₃	F ₄	F ₅	F ₆
F ₁	0.058	0.122	0.132	0.135	0.102	0.120
F ₂	0.175	0.138	0.253 (*)	0.220 (*)	0.169	0.220 (*)
F ₃	0.172	0.260 (*)	0.124	0.180	0.167	0.225 (*)
F ₄	0.109	0.207 (*)	0.117	0.073	0.110	0.140
F ₅	0.363 (*)	0.406 (*)	0.365 (*)	0.330 (*)	0.146	0.378 (*)
F ₆	0.179	0.251 (*)	0.277 (*)	0.186	0.182	0.124

Using the derived D (impact) and R (receptivity) vectors, the functional role of each factor was identified (Table 4). The $D - R$ value, or Prominence, signifies the factor’s total visibility and involvement within the system; a higher score indicates a more central role in the logistics network. Conversely, the $D - R$ value, or Relation, determines the factor’s net influence. Factors with a positive $D - R$ score are categorized as net “Causes,” acting as primary drivers that affect other variables. Factors with a negative $D - R$ score are identified as net “Effects,” indicating they are predominantly influenced by changes elsewhere in the system. This distinction is critical for prioritizing strategic interventions, ensuring that resources are first directed toward the most influential levers.

Table 4. Assessment of the influence and causality of factors.

Factor	D	R	D+R	D−R	Dominant Characteristic
F ₁	18.6695	18.0928	36.762	0.577	Cause
F ₂	18.6810	18.3576	37.039	0.323	Cause
F ₃	17.7669	17.9625	35.729	−0.196	Effect
F ₄	19.1324	17.8346	36.967	1.298	Cause
F ₅	18.4185	18.9255	37.344	−0.507	Effect
F ₆	17.8265	18.1563	35.983	−0.330	Effect

The comprehensive outcomes of the DEMATEL analysis are distilled into the causal diagram (Figure 1). This visual representation maps the prominence of each factor against its net relation, creating a hierarchical map of influence. By distinguishing between system drivers (high prominence/positive relation) and system outcomes (high prominence/negative relation), the diagram provides high-level strategic insight. It reveals exactly where managerial focus should be concentrated to achieve the most leveraged results in transitioning toward a sustainable and efficient reverse logistics model.

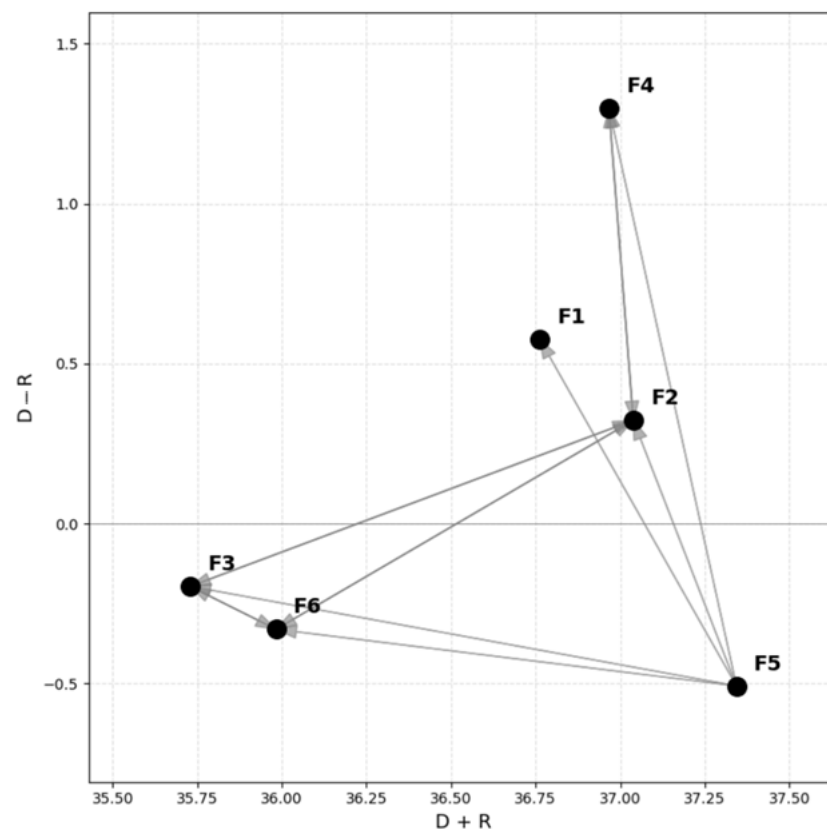


Figure 1. Causal diagram, where the arrows indicate the transmitted influence.

5. Sensitivity Analysis

The purpose of the sensitivity analysis was to examine whether the causal structure identified by the DEMATEL model depended on the evaluation provided by any individual expert. Since DEMATEL is based on expert judgments, it is important to determine whether the final results remain stable when one participant is removed from the aggregation process. If the exclusion of a single expert produces substantial changes in the prominence values or in the cause and effect classification of the factors, the interpretation of the model becomes more uncertain. On the other hand, small variations indicate that the aggregated matrix reflects the overall consensus of the expert panel instead of the opinion of a particular participant.

A sensitivity investigation was performed to evaluate the extent to which the aggregated influence scores depend on individual expert contributions. The purpose of this analysis is to determine whether the obtained values remain stable when the expert panel composition is modified or whether specific experts exert a disproportionate impact on the results.

Let m denote the number of experts involved in the evaluation process. In the present study, $m = 6$. The reference direct relation matrix was obtained by averaging the evaluations provided by the expert panel. This matrix was used as the baseline for the sensitivity analysis.

To examine the stability of the results, the reference matrix was compared with matrices recalculated after modifying the expert aggregation used in the analysis. The comparison focused on the variation in the aggregated influence values and on whether these changes affected the overall interpretation of the DEMATEL results.

$$\bar{z}_i = \frac{1}{m} \sum_{e=1}^m r_i^{(e)} \quad (9)$$

where $r_i^{(e)}$ represents the score assigned by expert e to relationship i .

To assess robustness, the reference matrix was recalculated for the sensitivity scenarios and compared with the original aggregated matrix.

$$\bar{z}_i^{(-G)} = \frac{1}{m - |G|} \sum_{e \notin G} r_i^{(e)}, |G| = 1 \quad (10)$$

The sensitivity of each relationship to expert exclusion was quantified by computing the absolute deviation between the reference mean and the recalculated mean:

$$\Delta_i^{(-G)} = \left| \bar{z}_i - \bar{z}_i^{(-G)} \right| \quad (11)$$

This deviation indicator provides a direct numerical measure of how strongly the aggregated result depends on the presence of a particular expert.

Rather than analyzing deviations at the level of individual relationships, the robustness of the evaluation matrix was assessed using the extreme deviation values obtained under each exclusion scenario. To provide a concise and informative robustness indicator, the maximum deviation observed across all directional relationships was retained for each exclusion scenario:

$$\Delta_{max}^{(-e)} = \max_i \left(\Delta_i^{(-e)} \right) \quad (12)$$

The numerical results show that the maximum deviation values remain consistently low across all exclusion scenarios. When excluding any individual expert, the observed $\Delta_{max}^{(-e)}$ values range between 0.20 and 0.40. These deviations are small relative to the full evaluation scale and indicate that the recalculated mean values remain closely aligned with the reference means obtained from the complete expert panel.

The highest deviations are associated with relationships characterized by low to moderate mean values, where individual expert assessments display greater dispersion. In contrast, relationships with high reference means exhibit negligible sensitivity to expert exclusion, reflecting strong agreement among experts. Relationships with high reference mean values exhibited only minor variations across the sensitivity scenarios, indicating a consistent level of agreement within the expert panel.

Regarding the acceptance criterion, there is no universally fixed threshold for sensitivity in DEMATEL-based expert analyses. Instead, robustness is commonly evaluated by comparing the magnitude of observed deviations to the underlying evaluation scale and to the typical dispersion expected in expert judgment studies. In this context, maximum deviations not exceeding 0.40 can be considered limited and methodologically acceptable, as they do not alter the relative interpretation of influence intensities or the qualitative structure of the causal relationships.

Based on the limited variation observed across the sensitivity scenarios, the aggregated evaluation matrix remained stable. The sensitivity analysis indicates that the overall interpretation of the DEMATEL model was preserved and that the identified causal relationships were not materially affected by the comparison scenarios.

In the present study, the sensitivity analysis showed that the exclusion of individual experts produced only limited changes in the calculated values. The relative importance of the factors remained largely unchanged, while the general causal structure identified by the DEMATEL model was preserved throughout the exclusion scenarios. The factors that acted as system drivers continued to occupy leading positions, whereas the factors classified as dependent remained within the effect group. These observations indicate that the relationships identified in the reference model are stable and are not driven by the judgments of a single expert.

From a methodological perspective, these results increase confidence in the proposed model. The sensitivity analysis confirms that the causal relationships reported in this study represent a consistent interpretation of the expert evaluations collected during the research. This supports the use of the identified hierarchy of factors when discussing both the theoretical implications of the model and its practical application in reverse logistics management.

6. Discussion

The DEMATEL analysis in this study outlines a clear causal framework for reverse logistics factors in e-commerce sustainability, positioning returns processing systems (F_2) and top management commitment (F_5) as the most communicative elements based on their elevated prominence ($D + R$) values of 37.039 and 37.344, respectively, which reflect substantial total influences captured in the matrix T with entries exceeding the $\alpha = 0.192$ threshold, such as F_2 's impacts on digital customer technologies (F_3) at 0.253 and return policies (F_6) at 0.220. These factors' high D and R scores underscore F_2 's role as a causal driver ($D - R = 0.323$) driving downstream efficiencies and F_5 's as a receptive yet centrally anchored effect ($D - R = -0.507$), receiving inputs from multiple sources while propagating strong outflows, for instance F_5 to transport routes (F_1) at 0.363.

Causal drivers further include transport routes (F_1) with $D - R = 0.577$, manifesting as the system's most isolated initiator with moderate outflows like 1.200 in the direct matrix A to F_3 , and effective materials management (F_4) boasting the highest $D - R = 1.298$ and influencing F_2 at 0.207 in T . Effect factors such as digital customer technologies (F_3) ($D - R = -0.196$), top management commitment (F_5), and return policies (F_6) ($D - R = -0.330$), are predominantly shaped by these drivers, as seen in F_3 's receptivity from F_2 at 0.260 and F_6 from F_5 at 0.378.

Since only a limited number of studies have examined reverse logistics relationships using DEMATEL, the following discussion focuses on interpreting the causal structure identified in the present study while relating the findings to the broader reverse logistics literature.

This causal prominence of returns processing systems (F_2) closely mirrors findings from Akdoğan and Coşkun [40], where empirical investigations across manufacturing firms identified processing capabilities as primary drivers of reverse flows, achieving 60–70% improvements in recovery rates through efficient sorting and disposition, much like our T -matrix highlighting F_2 's significant links to F_3 , F_4 , and F_6 , thereby validating its communicative driver status in e-commerce contexts. The central position of returns processing systems reflects their connection with several operational activities. Delays or inefficiencies at this stage affect the flow of returned products, the speed of customer refunds, and warehouse operations. Improvements in processing efficiency therefore extend beyond a single activity and influence the performance of the entire reverse logistics process.

Similarly, Srhir et al. [41] reinforce this through a sustainability framework, demonstrating that advanced processing systems reduce operational environmental impacts by 25–40% via value recapture, aligning precisely with F_2 's causal outflows in our model and emphasizing its non-isolated propagation unlike F_1 .

In contrast, while our results position F_2 as a moderate cause, de Brito et al. [42] frame processing more as an integrated response in frameworks, though their qualitative analysis supports its high interconnectivity akin to our prominence score.

Top management commitment (F_5) as the most well-anchored factor, despite its effect classification, finds robust support in Badenhorst [43], whose barrier analysis across logistics firms shows top-level commitment mitigates up to 70% of reverse logistics obstacles by integrating strategic support responsive to operational drivers, paralleling our high $R = 18.9255$ and inflows from F_2 and F_6 . The present findings suggest that management

commitment is closely linked to operational performance. When return processes function efficiently and organizational procedures are well established, management is more likely to support further investments and long-term improvements. This may explain why F_5 appears as an effect factor instead of a primary driver in the present study.

Kaynak et al. [44] quantifies this receptivity, with management involvement explaining 65% variance in lifecycle success influenced by processing and policies, directly corroborating F_5 's anchoring in our causal diagram.

Zhang et al. [45] further aligns, revealing CEO commitment moderates 30–50% of product return ecological impacts, though as an effect amplified by causes like F_2 , unlike some views positing it as pure initiator. Our emphasis on F_5 's effect nature contrasts slightly with Prasad [14], who lists it as a CSF driver in sustainable chains, but their survey data supports its centrality matching our prominence.

The identification of transport routes (F_1) as an isolated causal driver resonates with Gao et al. [4], whose vehicle routing optimization model minimizes emissions by 15–20% through independent route planning in reverse flows, echoing F_1 's positive $D - R = 0.577$ and low interconnectivity in our diagram, where it initiates but receives minimal feedback.

Effective materials management (F_4)'s strong causal role ($D - R = 1.298$) is affirmed by Alkahtani [46], a systematic review showing materials strategies like biodegradable packaging cut waste by 40% and drive recovery, consistent with F_4 's T -influence on F_2 at 0.207. This result can be explained by the role of materials management within the return process. Decisions related to sorting, packaging, and material recovery are made at the beginning of reverse logistics operations. These activities influence the efficiency of the following stages, including product inspection, transport organization, and inventory handling. This may explain why F_4 appears as one of the main driving factors in the causal structure.

For effect factors, digital customer technologies' (F_3) responsiveness aligns with Yas-pal et al.'s [2] study on data-driven reverse logistics, where digital platforms optimize 20% post-processing integration, dependent on F_2/F_5 as in our negative $D - R$. Dobrosel-skyi [35] confirms e-commerce returns tech efficacy hinges on upstream systems, reducing handling times by 15–25% reactively. Return policies (F_6) as effect matches Ezmigna [47], digital marketing-policy synergies cutting reverse costs 15–25% influenced by processing.

Divergences include de Brito [42], portraying transport routes (F_1) as more policy-responsive than isolated causes, based on qualitative flows. Osintsev et al. [48] DEMATEL-ANP shows higher F_1 centrality in green chains, contrasting our Romanian e-commerce isolation possibly due to infrastructure variances.

The Romanian e-commerce sector provides a specific operational context for reverse logistics. Although online retail has expanded rapidly in recent years, reverse logistics practices are still evolving, and companies differ in the level of digitalization and operational integration. These characteristics may explain why materials management and transport route optimization emerged as the main driving factors in the present study. Unlike several previous studies that describe top management commitment as an initial driver of reverse logistics implementation, the present results place this factor within the effect group. One possible explanation is that, in the Romanian e-commerce context, management support tends to develop after operational processes demonstrate consistent performance and measurable results. This suggests that improvements in operational capabilities may precede strategic commitment.

These alignments across sources validate our hierarchy, while the contrasts reveal contextual nuances. This suggests that focusing strategically on F_2/F_4 drivers will allow us to leverage F_5 amplification for long-term sustainability.

Overall, the identified causal structure suggests that improvements in reverse logistics should begin with the factors that act as system drivers. Changes introduced at these points are more likely to influence the remaining components of the system than actions directed toward effect factors. This interpretation supports the use of DEMATEL as a decision support tool because it identifies where managerial efforts are expected to produce the greatest impact.

Logistics improvements should begin with the factors identified as system drivers, since changes introduced at this level are more likely to influence the remaining components of the system. This confirms the value of the DEMATEL approach as a decision support tool for identifying priority areas for intervention.

The main contribution of this study is the identification of the causal relationships among reverse logistics factors in the Romanian e-commerce sector. The results show that effective materials management (F_4) is the main driving factor ($D - R = 1.298$), indicating that improvements in material recovery and packaging practices influence the performance of the entire return process. From a practical perspective, managers should prioritize investments in materials management because improvements at this stage support subsequent activities such as sorting, refurbishment, and transport planning.

Another important finding concerns top management commitment (F_5). Although it is often presented as a factor that initiates organizational change, the results of this study place it within the effect group ($D - R = -0.507$). This suggests that management support develops as operational processes become more effective and return systems become better organized. In this context, leadership commitment appears to be influenced by operational performance instead of acting as its initial driver.

The results also provide practical guidance for resource allocation. Companies with limited resources should prioritize transport route optimization (F_1) and materials management (F_4), since these factors influence several other components of the reverse logistics system. Focusing on these activities can improve operational efficiency and support sustainability objectives throughout the return process.

This study has several limitations. Although the expert panel met the requirements commonly applied in DEMATEL studies and included specialists with at least five years of experience in reverse logistics, the findings reflect the Romanian e-commerce context and should be interpreted accordingly. Different logistics infrastructures or regulatory environments may lead to different causal relationships. In addition, the analysis represents a single period of observation (December 2025 to January 2026) and does not capture future technological changes that may affect reverse logistics practices.

Future research could extend this work by applying hybrid approaches such as Fuzzy-DEMATEL or DEMATEL-ANP, examining the stability of the identified relationships over time, and comparing the causal structure across different countries or logistics environments. Further studies could also investigate how customer return behavior influences the relationships identified in the present model.

7. Conclusions

This research has established a comprehensive structural model for understanding the complex dynamics of reverse logistics within the e-commerce sector. By employing the DEMATEL methodology, the study moved beyond traditional descriptive approaches. It offers a rigorous mapping of the causal interdependencies that govern sustainability in supply chains. The analysis provides a clear distinction between the drivers that initiate systemic change and the effects that reflect organizational stability, providing industry practitioners with a clear roadmap for intervention.

The causal structure identified in this study reinforces the view that reverse logistics should be understood as an interconnected operational system. The results indicate that sustainability performance is influenced by the sequence in which operational improvements are implemented. Materials management and transport route optimization function as initiating elements because they shape the efficiency of downstream activities, including return processing, digital coordination, and managerial decision-making. This finding suggests that circular supply chains evolve through interactions among operational processes instead of independent improvements introduced within separate logistics functions.

This perspective extends previous studies that primarily identify barriers or success factors for reverse logistics. The present study demonstrates that these factors occupy different structural positions within the system and therefore contribute differently to the implementation of sustainable reverse logistics. Understanding these interactions provides a stronger theoretical explanation of how reverse logistics supports Circular Economy objectives and offers a basis for prioritizing managerial interventions according to their systemic influence.

The study demonstrates that achieving sustainability in reverse logistics is not the result of isolated operational improvements but a consequence of managing a network of interconnected variables. Through this systemic lens, the work illustrates how specific levers serve as the foundation for broader environmental and economic resilience. Specifically, for managers, the findings highlight that focusing on the “cause” (group materials management and transport optimization) is the most cost-effective way to improve the “effect” group, such as digital integration and management commitment. Furthermore, the research emphasizes the critical role of strategic alignment. It shows that even the most committed leadership requires robust operational drivers to amplify sustainability goals effectively.

From a practical perspective, the results suggest that managers should focus first on the factors identified as system drivers. Improvements in materials management should include better sorting procedures, standardized packaging for returned products, and more effective recovery of reusable materials. These actions can simplify downstream activities and improve the overall flow of returned products. Transport route optimization should also receive early attention through better route planning, load consolidation, and the use of digital tools for transport scheduling. Since these factors influence several other elements of the system, investments made at this level are more likely to improve the overall performance of reverse logistics than isolated actions directed toward individual operational issues. Organizations should therefore prioritize operational improvements before expanding investments in supporting activities such as digital integration or additional management initiatives.

The identified causal structure suggests that improvements in sustainable supply chain management should begin with the factors that influence the largest number of operational activities. The DEMATEL results indicate that materials management and transport route optimization create effects that extend throughout the reverse logistics system. This means that investments directed toward these activities are more likely to improve resource utilization, reduce operational inefficiencies, and support circular economy objectives than isolated improvements focused on individual downstream processes.

The main contribution of this study is not the identification of individual reverse logistics factors, as these have already been discussed in previous studies. The novelty lies in demonstrating how these factors influence one another within a single causal structure. The DEMATEL analysis shows that factors commonly examined independently actually occupy different structural roles within the system. For example, materials management functions as the main driving factor, whereas top management commitment behaves

as a dependent factor influenced by operational conditions. This perspective extends previous reverse logistics research by explaining the interactions among the factors instead of considering them as isolated determinants.

Beyond the numerical values generated by the DEMATEL model, the results provide a clearer understanding of how reverse logistics operates as an interconnected system. The analysis identifies the factors that initiate changes within the system and those that respond to these changes. This perspective helps explain why some operational improvements produce wider system effects than others and provides a basis for establishing priorities in sustainable reverse logistics management.

In conclusion, this work provides both academic and practical frameworks for navigating the transition toward a circular economy in e-commerce. For researchers, it offers a validated methodological path for analyzing logistics complexity in emerging markets. For industry practitioners, it serves as a strategic decision-making tool by identifying exactly where resources should be prioritized to maximize systemic impact and ensure long-term economic resilience against digital market volatility. Ultimately, the findings underscore that a proactive and integrated approach to reverse logistics is essential for companies. This is necessary to meet the dual challenges of increasing consumer demands and stringent environmental responsibilities in a digital global economy.

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