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Structural analysis of acute success factors of performance of reverse logistics relative to customer satisfaction

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Abstract
This paper aims to analyze the interactions between the factors influencing the performance of the reverse logistics chain. We attempted to explore the factors touching performance of reverse logistics relatively to customer satisfaction. We have proposed a structural analysis based on the MICMAC method to classify factors rendering to their direct/indirect influences and dependencies. The outcome of this research is to identify the relationship between the 31 variables used in the experimentation. It can be observed that this exploration may cooperative in reverse logistics policy development arrangement, motivated by customer necessity.
Keywords: Reverse logistics, performance, structural analysis, customer satisfaction

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1. Introduction

The current economic environment is characterized by increasingly volatile and unpredictable demand, an ever-increasing variety of products, shrinking life cycles, and increasing competitive pressure. One of the biggest challenges facing societies today is the need to respond to increased customer demand, in markets where competition from low-cost countries is becoming stronger and worse. To meet this challenge, industrial organizations are reorganizing themselves to offer differentiated products while improving their responsiveness and flexibility.

Companies form factories that collect raw resources from wholesalers and distribute completed merchandises to clients; trade shops have even distributions from vendors; Every time you purchase, rent, lease, borrow everything at all, someone has to create sure that all the quantities are transported together and distributed to your door. Logistics is the function that is responsible for this movement. It is in charge for the transport and storage of resources on their trip between dealers and clients.

People use different names for these chains of activities and organisations. Here we are emphasizing the movement of materials and will use the most general term of the supply chain. The supply chain concept was born in the 1990s when management techniques in the socio-economic world evolved from separate logistics to integrated logistics and subsequently to cooperative logistics (e.g. [1]). It is in this evolution of the environment that companies have turned to alliances and strategic partnerships to form logistics networks. These networks have changed the vision of competitiveness and survival of a fortress enterprise to that of a network of companies that coordinate and collaborate to achieve benefit (e.g. [2]).

The supply chain has been an area of interest for years for the scientific community. The evaluation of a logistics chain is one of the major priorities of companies, a task that remains difficult given the complexity of its systems (e.g.[3,4]). The logistic performance was evaluated only from a cost perspective, then the concepts of reliability, quality and lead times are included, and nowadays a much broader vision of performance has emerged taking into account environmental and social aspects (e.g. [5,6]). Indeed, today the purpose of the logistics chain is to respond to customer demand at the lowest cost and with the minimum impact on the environment.

Performance measurement is commonly definite as the manner of enumerating the efficiency and effectiveness of the act. Efficiency is the degree to which the client's necessities are encountered, while economic efficiency processes how a company's funds are used to reach a programmed level of customer satisfaction. To be sustainable, logistics chains need work within an accurate financial structure, as well as donate to the environment and society. Management of the Green or Sustainable Environmental Supply Chain has been considered as a zone where officialdoms and manufacturers can create a substantial influence to both economic and environmental development (e.g. [7,8]). Straightforward research using observed and case study research on accelerative sustainable logistics chains has undergone considerable growth over the past two decades. Normative, prescriptive and quantitative modeling labors on the prior sustainable chains have received far fewer attention (e.g. [9]), although four reverse logistics scheduling has expected a detailed search (e.g. [10]). The call for the progress and use of economic and optimization methods to other communally favored research such as sustainable chains research has continued (see, e.g. [11,12]).

The balance of these sizes can help societies plump to what extent they should yield each one based on structural, public, and competitive densities and necessities, a very significant stage towards decoupling economic development and degrading the environment at the Supply Chain level. The increased attention given to the issue of environmental management of the logistic chain guarantees the writing of this paper. As such, Green Logistic Chain (GLC) is essential for influencing the total environmental impact of all organizations involved in supply chain activities. In addition, GLC can contribute to improved performance in reverse logistics (see, e.g. [13,14,15]).

The green supply chain is about making efforts to measure and minimize the environmental impact of logistics activities (e.g. [16]). Authors, however, should distinguish green logistic from reverse logistics, although common interfaces. In this paper, we are interested in reverse logistics from the supply chain. Reverse logistics refers to activities dedicated to the processing of returned products until they are satisfactorily recovered or scrapped. Their recovery activities include reuse, repair, refurbishment, prefabrication and recycling, which must take place in specific sites that are of two different types: collection centers (stores where consumers deposit products used) and reprocessing sites (manufacture centers or repair or refurbishment centers). In this context, the design of in-stream networks requires the proper definition of transport axes for consumer return flow to reprocessing sites. Another characteristic to be taken into account in the design of reverse chains is the great degree of uncertainty accompanying the return of used products by consumers not only regarding quantities but also regarding quality. In most practical studies dedicated to reverse logistics, recovery systems aim at recycling raw materials or recovering energy.

Unfortunately, the literature concerning previous works and results in reverse logistics metric progress is rare. Recently Yadov and Barve [17] argue that Government policies and Organizational structure is the most directing factor which has the highest dynamic influence and the minimum dependence influence as it drives others factors and systems the base of interpretive structure model.

Structural analysis has undergone developments, to solve this type of problems, which have also benefited from the analysis of actors' games dealing both with variables and relationships (see, e.g. [18,19]).

The work proposed here is limited to the direct relations between the variables and therefore to the crossed impact matrices (MIC), even if the structural analysis went beyond this stage to study the indirect relations between the variables thanks to the cross-impact matrices.

The main contribution of this paper is twofold: First, the coordination of the different entities of the supply chain constitutes a current major challenge. Second, the line of research that we have exposed to this problem is to define a decision support tool for planning and identification of the greatest significant factors to clarify the performance of the reverse logistics relative to client satisfaction via structural analysis. The results confirm the choice of using the MICMAC method to identify the interactions between the factors influencing the performance of the reverse logistics chain.

The rest of the paper organized as follows: In Section 2 the description of the reverse logistics is provided. In Section 3 a structural analysis based on MICMAC methods is described as a solution methodology. Finally, we conclude the paper in Section 4.

2. Problem description

In this research, a reverse logistics structure with industrial / renovation, demonting, and removal services is expected in which the producer yields finished merchandises affording to demand and rheostats the flow of portions, goods and information in the system as well. Some of the products retailed to clients should be returned to the supply chain. Besides these difficulties, there is an excessive deal of uncertainty natural in the demand, the customers' capacity providers, and the proportion of kept goods that must be talked in the context of decision making. To formulate the complex multi-criteria problem above, an uncertain multi- objective mathematical model is expressed by the subsequent notations for groups, indices, parameters and decision variables.

Notations:

I : Index of providers, $i = 1, ..., I$

J : Manufacturing index, $j = 1, ..., J$

M : Party index, $m = 1, ..., M$

N : End products index, $n = 1, ..., N$

K : Index of objective functions, $k = 1, ..., K$

Parameters

$Sell_n$: Selling price unit of product, $n \in N$

$\cos t_{jn}$: unit production cost of product at the plant n, $j \in J$, and $n \in N$

$price_{im}$: unit price of a part m bought from the supplier i, $i \in I$ and $m \in M$

$ship_{ij}$: the transport cost of the supplier i to plant j, $i \in I$ and $j \in J$

inv_j : cost of holding inventory at the factory j, $j \in J$

$Setdis_n$: installation cost of a disassembly site for product n, $i \in N$

$disa_m$: disassembly cost of the unit for a part m, $m \in M$

$disp_m$: unit arrange cost for a part m, $m \in M$

$ref \cos t_{jm}$: the cost of renovating the unit for a part m at the factory, $j \in J$, and $m \in M$

$quality_{im}$: fraction of poor quality parts type M purchased from supplier i, $i \in I$ and $m \in M$

$delivery_{im}$: fraction of delivered parts end of type M bought from supplier i, $i \in I$ and $m \in M$

$econrisk_i$: the risk factors of the economic environment associated with supplier i, $i \in I$

$\overline{dem}_m$: the demand for the product n blurred, $n \in N$

req_m : requirements of the unit for a part m to produce a unit of product n, $m \in M$ and $n \in N$

$\overline{\sup \max}_{im}$: maximum available capacity fuzzy of a part m supplied by the supplier i, $i \in I$ and $m \in M$

$\sup \min_{im}$: minimum purchase quantity of a part m of the supplier i, $i \in I$ and $m \in M$

$reuse_m$: maximum percent reusable part m, $m \in M$

$\overline{return}_n$: fuzzy percentage of returned product n, $n \in N$

Decisions Variables

X_{ijm} : Part number m buy from the supplier or by the establishment j,

$i \in I$, $j \in J$ and $m \in M$

Y_{jn} :number of products n produced at the factory j,

$j \in J$, and $n \in N$

r_n : number of products returned n to be dismantled on the disassembly site, $n \in N$

O_m : Number of the part m obtained on the dismantling site, m $\in$ M

d_m : Part number m to be eliminated from the disassembly site, $m \in M$

ref_{jm} : Number of part m to be renovated at the factory j, $j \in J$, *and* $m \in M$

$$S_i = \begin{cases} 1 & \text{if the provider } i \text{ is chosen;} \quad i \in I \\ 0 & \text{otherwise,} \end{cases}$$

bd_n : binary variable for mounting site configuration for product n, $n \in N$

The mathematical model is presented as follows:

$$\max \mathrm{f}_1 = \sum_{j \in J} \sum_{n \in N} \left(sell_n - \mathrm{cos}t_{jn} \right) Y_{jn} - \sum_{i \in I} \sum_{j \in J} \sum_{m \in M} \left(price_{im} + ship_{ij} + inv_j \right) X_{ijm} - \sum_{n \in N} setdis_n bd_n$$
$$- \sum_{m \in M} (disa_m o_m + disp_m d_m) - \sum_{j \in J}^{n \in N} \sum_{m \in M} ref \ \mathrm{cos}t_{jm} ref_{jm} \quad (1)$$

$$Min\, f_2 = \sum_{i \in I} \sum_{j \in J} \sum_{m \in M} quality_m X_{ijm} \quad (2)$$

$$Min\, f_3 = \sum_{i \in I} \sum_{j \in J} \sum_{m \in M} delivery_m X_{ijm} \quad (3)$$

$$Min\, f_4 = \sum_{i \in I} econrisk_i X_{ijm} \quad (4)$$

Subject to :

$$\sum\nolimits_{j \in J} Y_{jn} \cong \overline{dem_n} \qquad \forall n \in N \quad (5)$$

$$\sum_{j \in J} req_{mn} Y_{jn} = \sum_{i \in I} X_{ijm} + ref_{jm} \qquad \forall j \in J, m \in M \quad (6)$$

$$\sum_{j \in J} ref_{jm} + d_m = o_n \qquad \forall m \in M \quad (7)$$

$$o_m = \sum_{j \in J} req_{mn} r_n \qquad \forall m \in M \quad (8)$$

$$\sum_{j \in J} X_{ijm} \le \sup \max_{im} S_i \qquad \forall i \in I, m \in M \quad (9)$$

$$\sum_{j \in J} X_{ijm} \ge \sup \min_{im} S_i \qquad \forall i \in I, m \in M \quad (10)$$

$$\sum_{j \in J} ref_{jm} \le reuse_m o_m \qquad \forall m \in M \quad (11)$$

$$d_m \le (1 - reuse_m)\, \mathrm{o}_m \qquad \forall m \in M \quad (12)$$

$$\sum_{j \in J} return_n Y_{jn} \ge r_n \qquad \forall n \in N \quad (13)$$

$$r_n \le B\, , \mathrm{bd}_n \qquad \forall n \in N \quad (14)$$

$$S_i\, , \mathrm{bd}_n \in \{0,1\} \qquad \forall i \in I, n \in N$$

$$X_{ijm}, \mathrm{Y}_{jn}, \mathrm{r}_n, \mathrm{o}_m, \mathrm{d}_m, \mathrm{ref}_{jm} \ge 0 \quad \forall i \in I, j \in J, \mathrm{m} \in \mathrm{M}, n \in N \quad (15)$$

The objective function (1) maximizes the total profit from the sale of finished products minus portions purchase costs from outside dealers, transportation costs, keeping parts inventory cost, the cost of installation products on the dismantling sites, the cost of dismantling the parts obtained, eliminating the cost price of useless parts, and the refurbishment of parts in the manufacturing services. The second objective function (2) minimizes the total number of defective quantities that is moreover equal to maximizing the total quality of portions bought from dealers. Third objective function (3) minimizes the total amount of close delivered portions obtained from the dealers.

Finally, the objective function (4) minimizes the total risk factors of the economic environment related to each provider.

Constraint (5) guarantees the total number of goods prepared from each type is equal to the uncertain demand characterised by a parameter for each type of goods. Constraint (6) describes the number of portions used to manufacture the final goods in each factory to be equal to the total number of renewed quantities from facelift sites and new amounts obtained from providers. The constraint (7) relates the number of pieces detached to be equal to the number of pieces refurbished and quantities settled, the constraint (8) displays the relationship among the number of pieces that can be gotten from return-born goods. Constraint (9) limits the total number of pieces procured from each provider to not exceed the maximum capacity of fuzzy suppliers. Also, the constraint (10) certifies the minimum obtaining amount prerequisite of each party from dealers. Constraints (11) and (12) boundary the proportion of returnable and arranged quantities that can be gotten from products kept to the dismantling plant. The constraint (13) displays the fuzzy ratio of products refunded to the scheme from products manufactured in total. The constraint (14) is for the beginning systems of the disassociation, and the constraint (15) bounds the selection decision variables of the suppliers and the configuration of the disassociation positions for each kind of goods to binary variables and all the other decision variables to be non-negative.

3. Solution methodology

The graphs theory inspires the structural analysis and simulations of operational research carried out shortly after the Second World War in the United States, in particular, the Rand Corporation for the needs of the American army.

The MICMAC software generates so-called influence-dependency plans. Each variable is associated with an influence and dependency indicator and is thus positioned on the influence-dependence plane. The factors are plotted on this plane according to their degree of influence and dependence of the matrix of indirect influences.

The steps of our proposed structural analysis are:

- The census of variables
- Identifying relationships in the structural analysis matrix
- SSIM
- Level position

Census of variables

This is an essential step as emphasized he also add that "the richness of structural analysis, along with its limits, lies in the choice of variables". The objective is to dissect the environment of the system to be studied by first identifying all its components and then, by structuring those, to obtain a list of exhaustive factors that are representative of the whole of this system, emphasizing Thus taking into account the different points of view. This gives a list of variables that must not exceed 80 factors, or parameters, for optimal exploitation.

This step is based on an open question such as the one suggested by Godet [20], for example: "What are the risk factors in the supply chain? ".

It is recommended at this phase to be as comprehensive as possible, and to be careful to avoid pasting everything in the obscure by describing the scheme. Besides brainstorming meetings and brainstorming, it is recommended to feed and combine the determination of variables overtalks with specialists. In a second step, it is necessary to examine the list of variables, to complete it if necessary or straight to remove some of them in order to obtain a consistent list. Afterwards, the first classification by categories makes it possible to distinguish between the variables. It is also necessary to establish a glossary, intended to formalize the consensual sense of the variables in the set. Although the descriptions need be simple sufficient to escape any false clarification, they will also be simply comprehensible for those who are external the set. Table 1 describes the variables used in the MICMAC analysis.

We identified a number of variables, and then they were grouped together to have 31 variables for the final analysis, which are listed in table 1 based on their sources.

Table 1. Variables description

Id	Description
V1	We are ready to dedicate our staff and resources to reverse logistics activities we are conducting with this client.
V2	Consistency of return procedure
V3	Facilitate contact and contact the return service staff.
V4	Tell the truth to our supplier (or make available to the supplier all available information).
V5	Facilitate the completion of the return form
V6	Make available to people to process information regarding the recovery of the product.
V7	Offer a significant guarantee offer to our customers.
V8	We hope that this client will understand all the problems we have and that we share with him / her
V9	The objective of the company: to preserve the relationship with its customers.
V10	Installing direct computer-to-computer links with key vendors
V11	We can count on this client by taking into account how our decisions and actions affect us
V12	This results in costs of compliance with environmental regulations due to our handling methods of handling
V13	Variety of options available for product return.
V14	Quick response to customer's return requirements
V15	Availability of collection centers
V16	We compensate our customer if the new product sent to replace the returned product did not arrive on time.
V17	Use of advanced information systems to track and / or accelerate shipments
V18	We acknowledge our return policies to be liberal
V19	Inter-organizational coordination obtained using electronic links
V20	Our strategy to deal with the return of merchandise improves our cost position compared to our closest competitors
V21	The use of technology allowed the processing of transaction information

V22	Real time information
V23	The functions, authority and responsibility of reverse logistics are documented in policies and procedures
V24	We tackle the problems of reverse logistics mainly with technologies that we have developed
V25	Realizing cost savings due to our reverse logistics activities
V26	Reverse logistics program évaluations in Our society rely on written standards
V27	Preparing the return product is easy
V28	Handling of the return without customer intervention
V29	Written procedures and guidelines are available for most reverse logistics related to work situations
V30	Relationship with supplier
V31	Overall satisfaction

The identification of the most important variables among these extracted variables, which explain the performance of the reverse chain using a scientific and proven methodology, as a factor of analysis and structural interpretation modeling using the interactive and contextual relationship among the extracted variables. The classification of these variables in disparate groups according to their power and dependence motor power. This helps in identifying the key drivers of reverse chain performance versus reverse chain performance.

Identifying relationships in the structural analysis matrix

It is not enough to identify the components of the system, because the latter only makes sense when we come to understand all the relationships that link the variables to one another. These relationships represent the explanatory environment of the system. Godet (2007) states that "Structural analysis involves linking variables in a double entry table (structural analysis matrix)." This matrix determines whether or not each column criterion influences each line criterion. The group that participated in the census of variables is the one that will fill the matrix.

Filling the matrix of structural analysis is intended to be both qualitative and quantitative. The qualitative filling is used to identify all relationships of direct influences between variables. For example, in the presence of variables B and C, these two questions should be asked:

1) Does variable B have a direct influence on variable C?
2) Does variable C have a direct influence on variable B?

When there is no direct influence relationship between two variables, it must be assigned the value 0 in the structural analysis matrix. When, on the other hand, there is a direct influence relationship between two variables, the relationship should be quantified by estimating its importance. In the case of a strong influence relationship, the value three must be assigned. The value two was assigned when it was an average influence relationship and the value 1 when s was acting in a weak relationship of influence.

This is a particularly difficult stage. The aim is to identify the direct influence relationships between the variables. It is at this level that all the subtlety of analysis lies: the distinction between relations of direct influences and indirect relations of influence. These should not be taken into account when identifying relationships.

Identification of key variables when the matrix is completed, the degree of motor function and the degree of dependence of the criteria must be counted.
- Totalizing each column obtains the degree of motricity of each parameter.

- The degree of dependence is obtained by totaling the lines.
The data thus obtained indicate which are autonomous, influential and dependent variables.

Structural self-interaction Matrix (SSIM)
The matrix of direct/indirect and potential influences

The MICMAC software distinguishes between the direct influence matrix (DIM) and the potential direct influence matrix (PDIM). The first (DIM) is the structural analysis matrix also known as the input matrix, the influences are noted from 0 to 3, with the possibility of signaling potential influences: 0: No influence, 1: Low, 2: Average, 3: Strong and P: Potential.

The second (PDIM) represents the current and potential influences and dependencies between variables. It complements the MID matrix by taking into account the possible relationships in the future (potential influences) with the influences are noted from 0 to 3, with 0: No influence, 1: Weak, 2: Medium and 3: Strong and P: Potential. The results of the study are given according to the type of influence (direct, potential direct, indirect or potential indirect). The MICMAC software presents the characteristics of the matrix in a table, studies the stability of the corresponding matrix, gives the sums in rows and columns of these matrices in a table, and presents by two planes influences / dependencies on the one hand direct and on the other hand potential direct and two graphs of the direct and potential direct influences.

As can be expected, the classifications of variables by decreasing motor/influence (or by dependence) are generally modified. However, experience has shown that these rankings become nearly stable after three or four power elevations, and they emphasize the importance of certain variables according to their indirect influences.

The comparison of rankings (direct, indirect, and potential), obtained by simple projections on the axes of the planes, is interesting for the research of the main determinants of the phenomenon studied and of its most sensitive parameters.

The comparison of direct, indirect and potential rankings confirms the importance of certain variables, but also leads us to discover that other variables, which we think are not important, play a preponderant role by their indirect actions. It would be a serious mistake to neglect them during the explanatory analysis. Variables (or factors) of risk are described previously; they are in the order of 30. It is a matter of prioritizing them (to identify the most critical variables or the key variables). The first step is to enter the MID direct influence matrix into the MICMAC software. The results of the study concern the variables of direct and indirect influences / dependencies.

Characteristics of the Direct Influences Matrix DIM

MICMAC combines the characteristics of the direct influencing matrix in Table 2. The latter presents the numbers 0, 1, 2, 3 and 4 of the matrix and displays the calculated fill rate by making the ratio between the number of DIM values different from 0 and the total number of elements of the matrix.

Table 2: Characteristics of DIM

INDICATOR	VALUE
Matrix Size	31
Number of iterations	4
Number of zeros	828
Number of one	62
Number of two	29

Number of three	42
Number of P	0
Total	133
Fill Rate	13,83975%

The input matrix for the MICMAC method is given in Table 3.

Table 3: Structural self-interaction Matrix (SSIM)

	1 : v1	2 : v2	3 : v3	4 : v4	5 : v5	6 : v6	7 : v7	8 : v8	9 : v9	10 : v10	11 : v11	12 : v12	13 : v13	14 : v14	15 : v15	16 : v16	17 : v17	18 : v18	19 : v19	20 : v20	21 : v21	22 : v22	23 : v23	24 : v24	25 : v25	26 : v26	27 : v27	28 : v28	29 : v29	30 : v30	31 : v31
1 : v1	0	0	3	0	0	3	0	1	2	0	0	0	1	3	2	1	0	0	0	1	0	2	0	0	1	0	2	2	0	0	3
2 : v2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3 : v3	3	0	0	0	2	0	0	1	2	3	0	0	2	2	1	0	3	0	0	0	0	1	0	0	0	0	0	0	0	3	3
4 : v4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5 : v5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
6 : v6	3	0	3	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	0	0	2	2
7 : v7	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
8 : v8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9 : v9	1	0	1	0	1	1	3	1	0	0	0	0	1	2	2	0	2	0	0	0	1	0	0	0	0	0	1	0	0	0	1
10 : v10	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	3	1
11 : v11	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12 : v12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13 : v13	1	0	1	0	1	1	1	0	0	0	0	0	0	1	3	3	3	0	0	1	1	0	0	0	0	0	1	2	0	0	2
14 : v14	3	0	3	0	3	3	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	2
15 : v15	2	0	1	0	0	1	0	0	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
16 : v16	1	0	0	0	0	0	3	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
17 : v17	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	2
18 : v18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19 : v19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3	1	0	1	1	0	0	0	0	0	0
20 : v20	0	0	1	0	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	2	0	0	1	0	0	0	0
21 : v21	0	0	0	0	0	3	0	0	0	3	0	0	0	2	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	1	2
22 : v22	1	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	3	0	0	0	2	0	0	0	0	0	0	0	0	3	1
23 : v23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24 : v24	1	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	3	0	0	0	2	0	0	0	0	0	0	0	0	1	1
25 : v25	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
26 : v26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27 : v27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28 : v28	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
29 : v29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30 : v30	0	0	0	3	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31 : v31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

MICMAC calculates the sums of rows and columns and classifies them in Table 4, so we can identify motor variables and dependent variables.

Table 4: Sums of rows and columns of DIM

Variable N°	Total of rows	Total of columns
1	27	19
2	0	0
3	26	14
4	0	3
5	3	9
6	16	13
7	9	7
8	0	4
9	18	21
10	7	14
11	2	0
12	0	0
13	22	6
14	18	12
15	9	10
16	10	7
17	6	15
18	0	0
19	9	0
20	9	9
21	14	10
22	13	11
23	0	0
24	10	3
25	6	2
26	0	0
27	0	6
28	6	4
29	0	0
30	6	14
31	0	33
TOTAL	246	246

The results show that the variable "We are willing to devote our staff and resources to the reverse logistics activities we are conducting with this client" (V1) to the sum of the highest lines (27) variable motor. The variables "General Satisfaction" (V31), are the dependent variables since they have the sums of the highest columns (33).

Level positions
Map of direct and indirect influences/dependencies

The MICMAC software generates so-called influence dependency plans. Each variable is associated with an influence and dependency indicator and is thus positioned on the influence-dependence plane. The factors are plotted on this plane according to their degree of influence and dependence of the matrix of indirect influences (e.g. Figure 1).

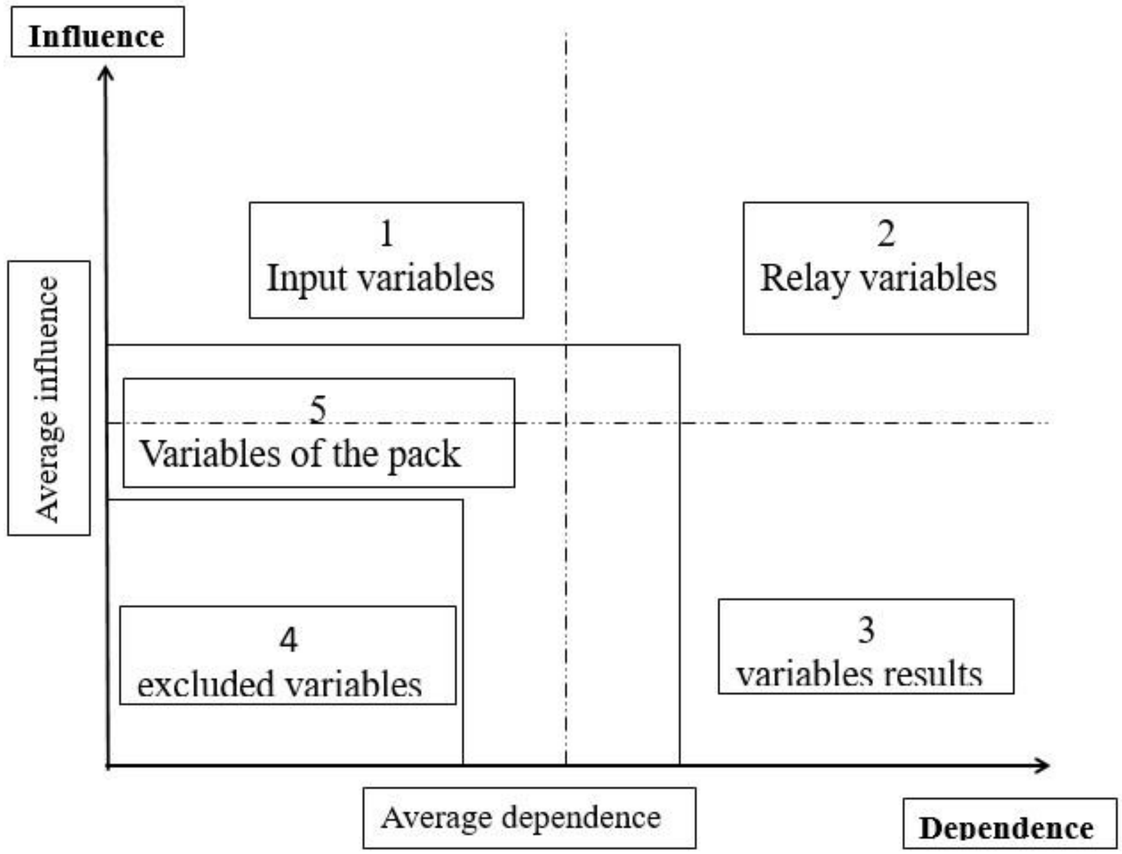

Figure 1: Types of influence / dependence variables

<u>The input or influent variables:</u> located in the northwest frame. These are the highly influential variables that are not dependent on other system variables. These are the explanatory variables of the system studied and are the most crucial elements. Surrounded by them, there are usually environmental variables that powerfully form the system, but in common they cannot be measured. Rather, they will turn as an issue of inertia.

<u>Relay variables:</u> These are very influential and highly dependent variables. The actions they take will be reflected throughout the system. They are the stakes.

Of the system studied, around which actors will fight because of their unstable nature. In addition, a distinction should be made in this set between:

- Interest variables, further exactly positioned nearby the diagonal, which will have a solid chance to awaken the thirst of the foremost players, from their uneven characters, they are an impending control point for the structure,
- Target variables, placed below the diagonal reasonably than along the southern border of the North, are further dependent than influential. Therefore, we can consider them, to an assured level, as the result of the evolution of the structure. Conversely, a deliberate action can be taken on them in order to develop them in the wanted technique. Therefore, they characterize objectives for the whole structure, slightly than completely programmed significances.
- The results or dependent variables: positioned in the Southeast of the map, are both weak and very dependent. The evolution of these variables is explained by the evolution of the input variables and the relay variables. They are output variables of the structure.

Excluded or autonomous variables: These variables are not very influential and not very dependable. They do not have much impact on the evolution of the system. These variables are located within the Southwest and seem to be out of proportion to the system because they do not allow us to stopover a foremost growth suffered by the structure, nor to yield benefit of it. Conversely, a distinction need be made in this set among:

- disconnected variables located close the origin of the alignment, the growth of which appears rather to be omitted from the overall dynamics of the system,
- Secondary variables which, though rather self-directed, are further influential than dependent. These variables are positioned in the South-West context, well overhead the diagonal, and can be used as temporary secondary variables, or as points of application for likely complementary processes.

Platoon variables: These are moderately influential and moderately dependent variables. It is not possible to determine their role in the system. Thus, these classes vary from each other depending on the exhaustive role of the variables they can show in the dynamics of the scheme.

Level position Map of influences / direct dependencies

It is principally recommended to compare the locations of the variables derived from the direct and indirect classifications (MICMAC). This presentation has the benefit of succeeding the global, but relatively superficial, assessments of the direct classification variables. They allow, among other things, the appearance of variables hidden from the light. Such a result requires management to take these variables into account better and to analyze them further. Therefore, MICMAC provides the displacement map, a presentation to compare the positions of the variables.

This map is determined from the matrix of direct influences DIM (Figure 2), whose abscissa axis represents the degree of dependence and the ordinate axis represents the degree of influence. The projection of risk variables regarding direct influences/dependencies shows that:

• The input variables located to the northwest are "We are willing to dedicate our staff and resources to the reverse logistics activities we are conducting with this client" (V1) located in the northwest frame. Highly influential and not very dependent, this variable remains crucial for the system and cannot be controlled.
• The results or dependent variables "General satisfaction" (V31) located in the south-west framework, is both weakly influential and highly dependent. It is the output variable of the system.

Graph of direct influences

MICMAC also generates the graph of direct influences (Figure 3). This plan is determined from the matrix of direct influences. It gives a clearer view of the most important influences by diagramming by an arrow the relationship between the variable i and the variable j and indicating on each arrow the degree of influence.

The matrix of indirect influences IIM

The Matrix of Indirect Influences (IIM) corresponds to the matrix of the DIM matrix great in influence, by consecutive iterations. From this matrix, a new classification of the variables highlights the greatest significant variables of the structure. Indeed, the hidden variables are detected. This permits us to learn the diffusion of impacts by routes and feedback rounds, and so to rank variables: in order of influence, enchanting interested in the number of routes and loops of distance (1, 2,…, n) from each variable; in order of dependence, winning into account the number of routes and loops of distance(1, 2,…, n) arriving on each variable. The classification becomes established in general from multiplication to the order 3, 4 or 5.

As for direct influences, MICMAC calculates the sums of rows and columns of the IRM. They are given in Table 5.

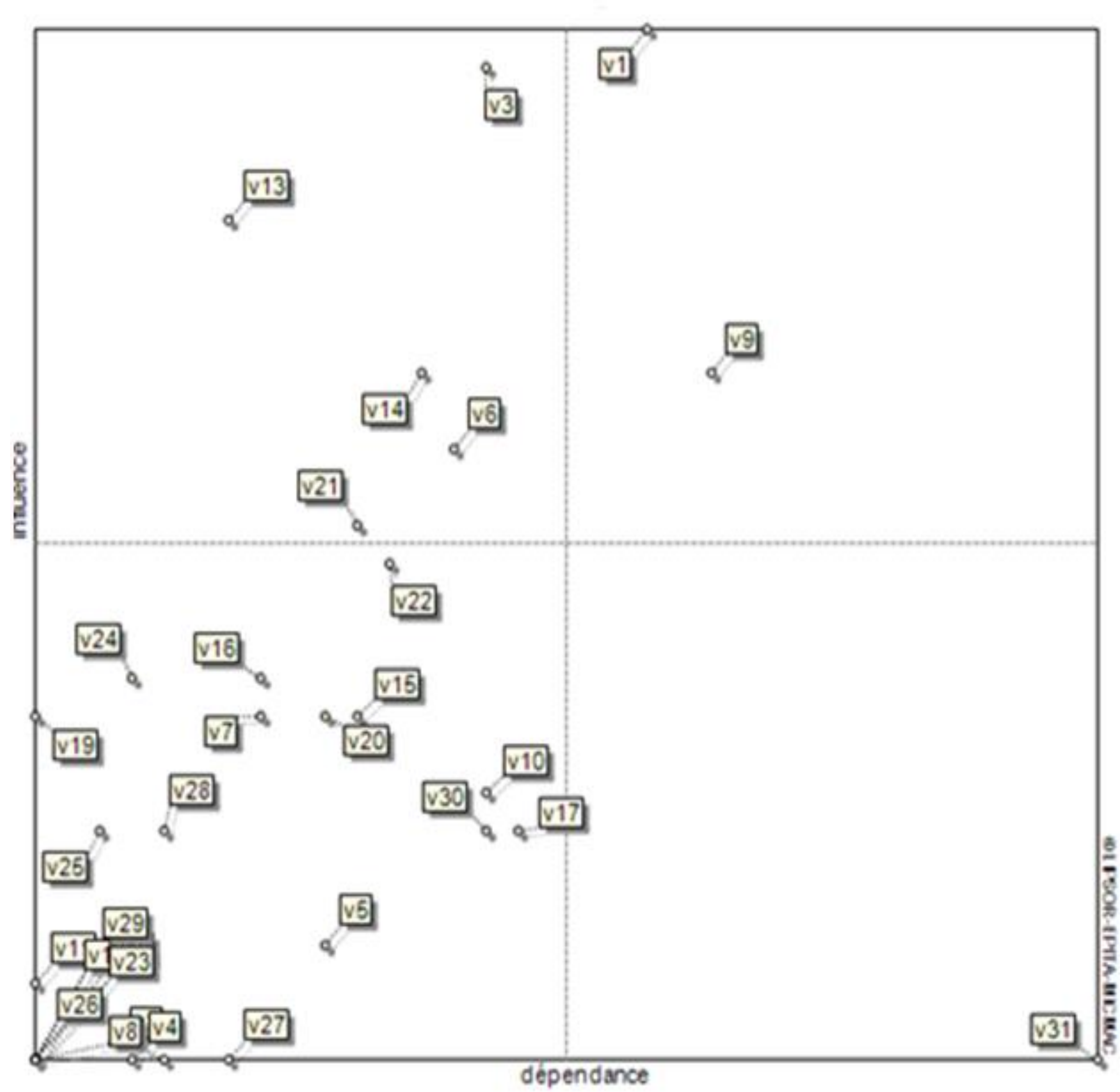

Figure 2: Map of influences / direct dependencies

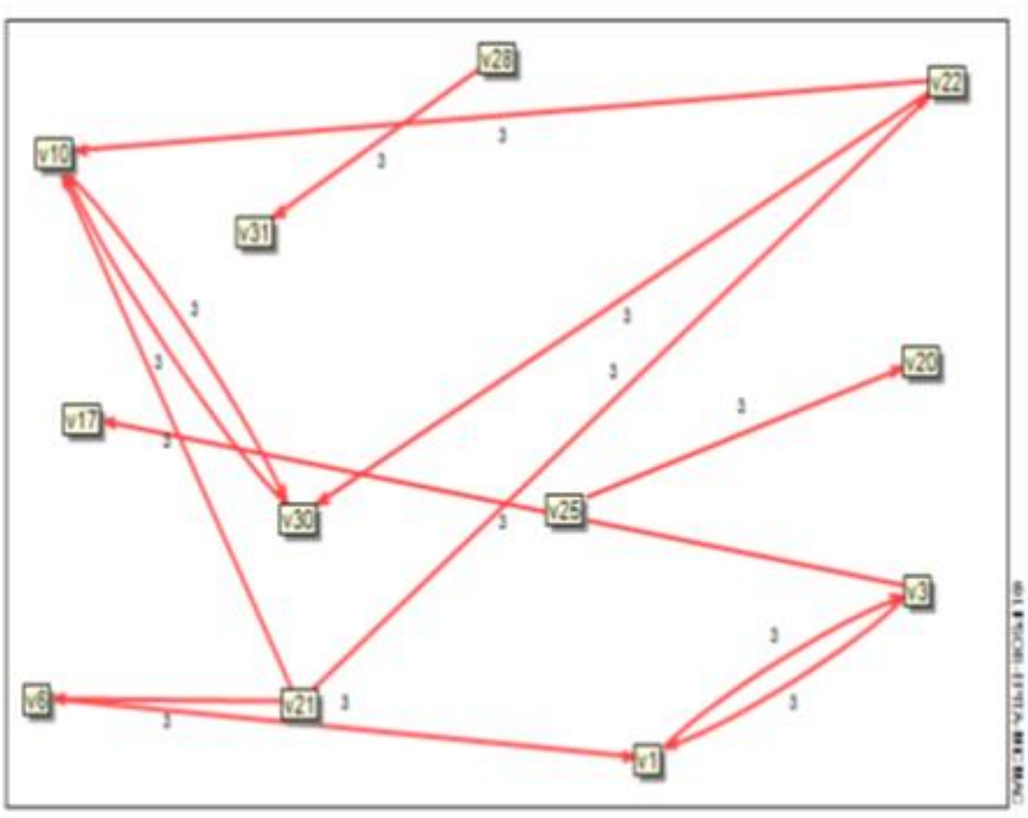

Figure 3: graph of direct influences

Table 5. Sum of rows and columns of IIM

Variable N°	Total of rows	Total of columns
1	518314	325940
2	0	0
3	403892	279993
4	0	65379
5	0	163656
6	368286	239774
7	126591	126561
8	0	82248
9	322986	343124
10	85664	216423
11	44692	0
12	0	0
13	337398	134112
14	408026	244805
15	250885	202992
16	161599	96207
17	80584	240959
18	0	0
19	139793	0
20	176537	68349
21	229070	99288
22	134307	189456

Variable N°	Total of rows	Total of columns
23	0	0
24	122791	11878
25	125905	28029
26	0	0
27	0	125337
28	84471	79494
29	0	0
30	22938	250401
31	0	530324

These results showed us that the variables "We are ready to dedicate our staff and resources to the reverse logistics activities we are doing with this client…»(V1) and" Facilitate to contact and reach back service staff. "(V3) are driving variables since they have the largest sums of lines. While the variables "Quick Response to Customer Return Requirements" (V14), are the most influenced variables, also called dependent variables because they have the highest sums of the columns.

Map of indirect influences/dependencies

The projection of the risk variables on the indirect influence/dependence scheme (Figure 4) shows that:

• Incoming variables located in the northwest are: "Making people available to process product recovery information." (V6), "Variety of options available for product return." (V13) and "Quick Response to Customer's Return Requirements" (V14) located in the northwest setting. These are the variables that are very influential and not very dependent on the other variables of the system. These are the explanatory variables of the studied system, and they are the most crucial elements. These variables cannot be controlled.

• The outcome or dependent variables are: "Overall satisfaction" (V31) located in the south-east frame, are at a similar time slight influential and very dependent. The evolution of these variables is explained by the progress of input variables and relay variables. There are output variables of the scheme.

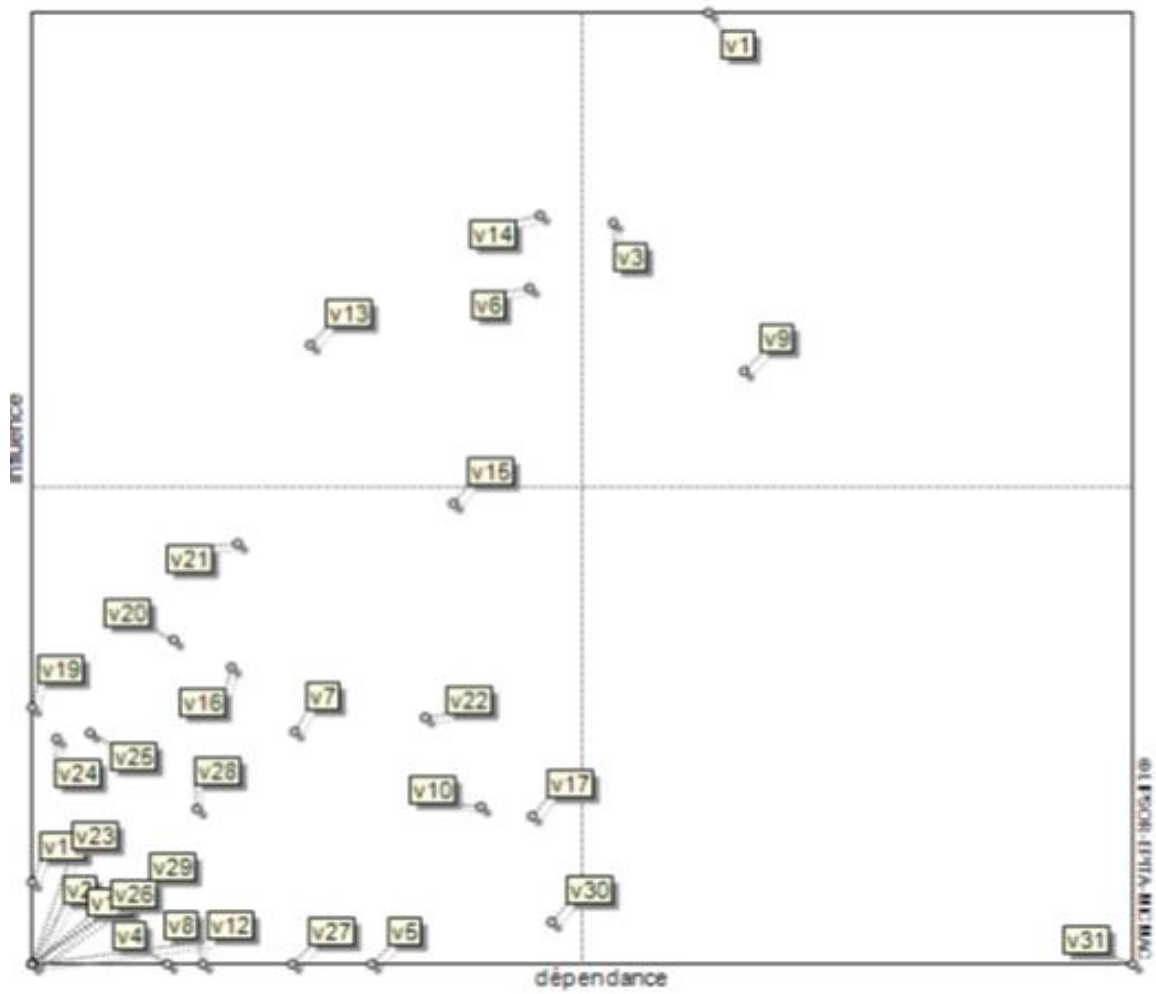

Figure 4: Map of influences / Indirect dependencies.

Graph of indirect influences

According to figure 5, the most important influences are respectively those of the variables (V3) "Facilitate contacting and joining the staff of the return service." And (V14) "Rapid response to the needs of the customer's return" on the Variable (V31) "Overall Satisfaction", and come after Variable Indirect Influences (V1) "We are ready to dedicate our staff and resources to the reverse logistics activities we conduct with this client." on the variable (V31) "Overall satisfaction".According to this MICMAC analysis, the most dependent variable (V31) is the most critical variable.

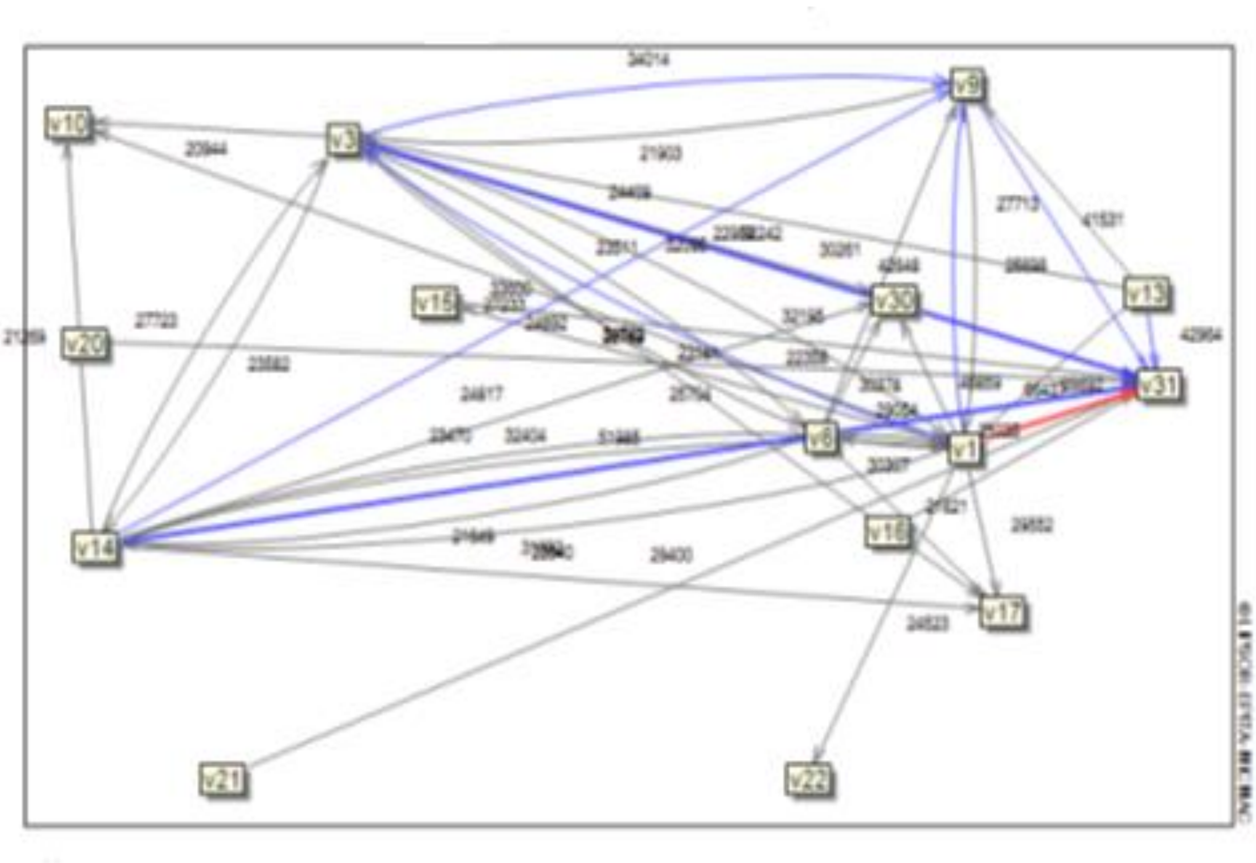

Figure 5: Graph of indirect influences.

4. Conclusions

Performance evaluation in reverse logistics can have various impacts on a community's economic development goals. Therefore, the economic benefit of the good identification of the factors influencing the performance of the reverse logistics and the implication of determinate the relationship and the interaction of the variables is shown by the result given in the MICMAC analysis.

We examine the scope of further research. In this study, we have discussed the performance of reverse logistics in relation to customer satisfaction using a structural analysis basis on the MICMAC software. The MICMAC method is applied to explain better the direct and indirect relationships between the 31 logistics chain variables described in section 3 for customer satisfaction, and to determine the highest priority variables. This prioritization is a tool to differentiate influential and dependent reverse logistics chain variables and to identify mutual relationships that will help them focus on the key variables that are most important. The results showed that the most important inverse logistic chain variables that could be considered as relay variables are the variables (V1) and (V9).

Future research should further develop a mathematical model for the reverse logistics problem. The selection of input variables, allowing the automatic selection of limits based on the number of variables, may be used in future statistical studies of the variables, and the statistical validation of the model.

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