Analyzing Cross-impact Matrices for Managerial Decision-making Problems with the DEMATEL Approach

Shailesh Tripathi, Nadine Bachmann, Manuel Brunner and Herbert Jodlbauer
University of Applied Sciences Upper Austria Wehrgrabengasse 1-3, 4400 Steyr, Austria

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Abstract: Cross-impact matrices define pairwise direct impacts between variables representing the complexity of various social, economic and technological systems. Business and management-related research primarily utilizes the row and column sums of direct impact matrices to identify critical, influential, dependent, neuter, and inert variables. However, the impact of drivers and outcomes in complex systems is usually difficult to interpret accurately without considering the indirect impact of variables. This paper considers all impacts of direct and indirect impact paths (known as the total impacts) between variables using the decision-making trial and evaluation laboratory (DEMATEL) approach for direct impact matrices in which the rank order remains stable (i.e., a stable equilibrium state exists). Numerical experiments show that the rank order of variables and their role (influence or dependence) can change significantly when considering total impacts between variables compared with when considering direct impacts only. This analysis can be used to support management in strategic planning and decision-making, e.g., in an international business environment: Management should attempt to obtain the total impacts matrix defining all direct and indirect impacts that determine the rank order on which informed decisions are subsequently based. The results presented in this paper indicate that impact paths between variables should be incorporated into the system with an in-depth domain understanding. This enables the realistic capture of impacts and the establishment of a stable state for obtaining an unbiased understanding of the roles of variables.

1 INTRODUCTION

As decision-makers, managers are faced with strategic challenges when projects and processes are affected by factors representing the complexity of interdependence in business model innovation, product innovation, strategy development, or reorganization, as these factors are usually difficult to understand and interpret. Cross-impact methods are commonly used as analysis and decision support tools in such cases. When few statistical or empirical data are available, these methods enable theory-driven and expert-oriented systems modeling (Panula-Ontto & Piirainen 2018; Weimer-Jehle, 2006). Expert judgments are processed and synthesized in a systematic, formalized, and structured manner, with the aim of identifying both direct and indirect impacts between identified variables (Asan et al. 2004). In contrast to the widespread use of direct impact matrices in the cross-impact approach, few studies (Arcade et al., 1999; Zimmermann & Eber, 2014; Jodlbauer, 2020; Jodlbauer et al., 2021) have addressed powered impact matrices.

This study investigates the cross-impact approach of using the total impact matrix, which considers all direct and indirect impacts from a given direct impact matrix obtained by the decision-making trial and evaluation laboratory (DEMATEL) approach (Gabus & Fontela, 1972). This study draws on Gordon and Hayward's (1968) cross-impact approach, Vester and Hesler's (1982) sensitivity model, and Godet's (1987) MICMAC method. We present an analysis based on simulated matrices of different orders that remain stable when all direct and indirect impacts are considered. Numerical experiments show that the rank order of variables in the total impact matrix, as compared with the direct impact matrix, can change significantly depending on their categorization into influential and dependent variables. This study attempts to present a numerical analysis method that can assist management in strategic planning by emphasizing the importance of using the total impact

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matrix for decision-making. In addition, it lays the foundation for future empirical research that applies the proposed method in practice. The following sections provide an overview of cross-impact analysis, discuss the current state of research, and present the research questions.

1.1 Cross-impact Analysis

Based on direct impact matrices, Gordon and Hayward (1968) introduced the cross-impact approach. The model starts with the definition of the relevant variables $V_1, V_2, \dots, V_n$. According to Vester and Hesler (1982), the pairwise influence between the variables is coded using values of 0, 1, 2, or 3:

$$a_{i,j} = \begin{cases} 0 & V_i \text{ has a negligible impact on } V_j \\ 1 & V_i \text{ has a small impact on } V_j \\ 2 & V_i \text{ has a proportional impact on } V_j \\ 3 & V_i \text{ has a great impact on } V_j \end{cases} \qquad (1)$$

In general, the influence is not commutative, i.e., $a_{i,j} \neq a_{j,i}$. The influence values are summarized in the so-called direct impact matrix A:

$$A = \left(a_{i,j}\right)_{i=1,\dots,n}^{j=1,\dots,n} \in \{0,1,2,3\}_n^n$$
$$\text{and}$$
$$a_{i,i} = 0 \text{ for all } i = 1,\dots,n$$
$$(2)$$

The direct impact matrix describes the pairwise direct impact between each pair of variables, and can be interpreted as the adjacency matrix of the weighted direct graph describing the pairwise direct impact between the variables (nodes of the graph). For further analysis, the active sum (*AS*), passive sum (*PS*), *Q*-value, and *P*-value are defined as follows (Godet & Roubelat, 1996):

$$\begin{aligned} AS_i &= \sum_{k=1}^{n} a_{i,k} && i-th \text{ active sum (sum of the } i-th \text{ row of the matrix } A) \\ PS_j &= \sum_{k=1}^{n} a_{k,j} && j-th \text{ passive sum (sum of the } j-th \text{ column of the matrix } A) \\ Q_i &= \frac{AS_i}{PS_i} && i-th\ Q\text{-value (quotient active sum over passive sum)} \\ P_i &= AS_i PS_i && i-th\ P\text{-value (product active sum by passive sum)} \end{aligned} \qquad (3)$$

AS can be interpreted as the weighted outdegree of the $i-th$ variable (node), whereas *PS* refers to the weighted indegree of the $i-th$ variable (node). A variable with a high *AS* value has a significant impact on all other variables, and vice versa. A variable with a high *PS* value is strongly influenced by the other variables, and vice versa. The Q -value reflects these categories, as the variable with the highest Q -value has the greatest overall impact on the other variables, i.e., it is the most active variable, while the variable with the smallest Q -value is most dependent on the other variables, i.e., it is the most passive variable. Active variables can be used to control or improve the system. It is important to be able to manage active variables, otherwise there is a risk of losing control of the system. Passive variables can be considered as output variables that measure success.

The P -value provides a measure of relevance. A variable with a high P -value has a great impact on the other variables and is strongly influenced by them. Variables with high P -values are referred to as critical variables and require the highest level of management attention. Critical variables and their relationships have to be understood to ensure the successful configuration and management of the system. Variables with small P -values are called inert variables and should not be the focus of management. In the so-called influence–dependency chart (Godet and Roubelat, 1996), the system, variables, and their relationships or significance can be visualized (see Figure 1). The x- and y-axes of the influence–dependency chart represent the passive sum and the active sum of the variables, respectively.

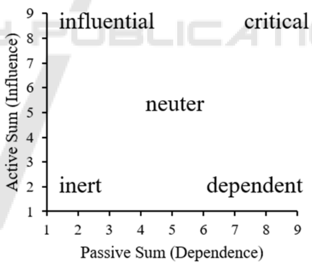

Figure 1: Influence-dependency chart.

The influence–dependency chart and distinguished between five categories of variables: critical, influential, dependent, neuter, and inert. The critical variables are those at or near the upper-right corner. Critical variables are affected by and impact many other variables. They are the most important variables to be considered and can be expressed as stake variables. Influential variables are located at or near the upper-left corner. These variables influence many other variables in the system, but are relatively less affected by other variables. They can be expressed as determinant variables. Dependent variables are positioned at or near the bottom-right corner. Dependent variables are more affected by the system than they affect it. They can be expressed as result variables to be monitored. Inert variables are located at or near the bottom-left corner. These have little influence on and low dependency on other variables. They are relatively unconnected to the system and can therefore be excluded from the impact matrix. Neuter variables are averagely influential and/or dependent variables. Nothing definite can be said about them. A similar division of variables can be found in Linss and Fried (2010), who use categories of reactive, critical, inert, and active.

To illustrate the cross impact analysis method, an example based on Vester (2000) is presented. For better comprehensibility, only the first four variables regarding urban development are utilized: attractiveness for recreation (V_1), need for leisure facilities (V_2), frequent use of open spaces (V_3), and variety of plant species (V_4). The relationships between these variables can be shown by a directed weighted graph called an effect–cause diagram (see Figure 2), or equivalently by the direct impact matrix (see Table 1).

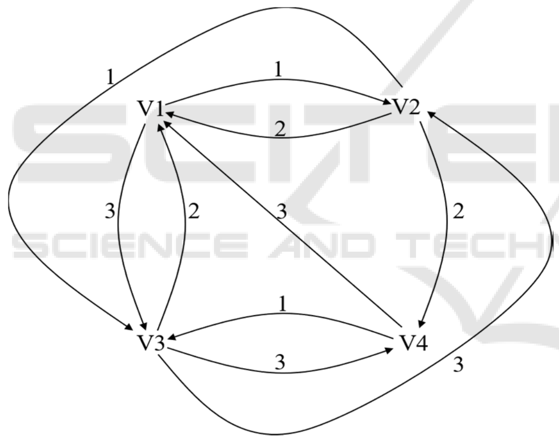

Figure 2: Effect-cause-diagram for the simple example.

Figure 2 shows the effect–cause diagram (weighted directed graph) for the first four variables discussed in Vester (2000). Table 1 presents all pairwise impacts, AS values, PS values, Q -values, and P -values. Figure 3 illustrates the four variables in the influence-dependency chart. Variable V_3 has the highest AS and the highest Q -value (i.e., the highest impact on all other variables), as well as the highest P -value (i.e., most critical variable). Variable V_1 has the smallest Q -value as well as the highest PS (i.e., influenced the most by all other variables). V_2 and V_4 both have the smallest P -value (i.e., most inert variables).

Table 1: Corresponding impact matrix for the simple example.

	V1	V2	V3	V4	AS	P
V1	0	1	3	0	4	28
V2	2	0	1	2	5	20
V3	2	3	0	3	8	40
V4	3	0	1	0	4	20
PS	7	4	5	5		
Q	0.57	1.25	1.60	0.80		

There are many other models similar to Vester's sensitivity method (Vester & Hesler, 1982). The analysis of several scenarios by Gausemeier et al. (2001) is based on an impact matrix with the same structure as Vester's impact matrix:

$$A_{\text{Vester}} = \left(a_{i,j}\right)_{i=1,\dots,n}^{j=1,\dots,n} \in \{0,1,2,3\}_n^n$$
and
$$a_{i,i} = 0 \text{ for all } i = 1,\dots,n \tag{4}$$

The cross-impact approach (Gordon & Hayward, 1968) utilizes a transfer matrix describing the pairwise probability of the occurrence of an event that is dependent on another event:

$$A_{\text{cross impact}} = \left(a_{i,j}\right)_{i=1,\dots,n}^{j=1,\dots,n} \in [0,1]_n^n$$
and
$$a_{i,i} = 0 \text{ for all } i = 1,\dots,n \tag{5}$$

Godet (1987; 2000) developed a scenario analysis whereby the structural analysis uses the impact matrix

$$A_{\text{Godet}} = \left(a_{i,j}\right)_{i=1,\dots,n}^{j=1,\dots,n} \in \{0,1\}_n^n$$
and
$$a_{i,i} = 0 \text{ for all } i = 1,\dots,n \tag{6}$$

It does not matter which coding the weighting has—as long as $a_{i,j} \geq 0$ and $a_{i,j} = 0$, the model developed in section 2 is applicable.

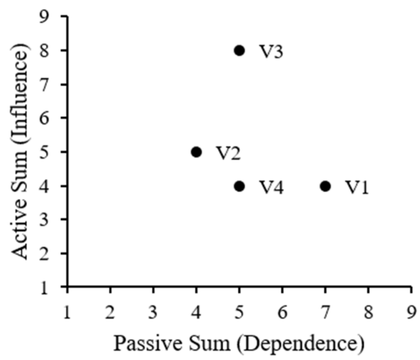

Figure 3: Corresponding influence-dependency chart for the simple example.

1.2 State of Research and Research Questions

The various applications of the cross-impact approach or similar methods cover different areas such as social network analysis (Wasserman & Faust, 1994), international business networks (Bolívar et al., 2019; Caraiani, 2013; Ho & Chiu, 2013; Joseph et al., 2014), project management (Frahm & Rahebi, 2021; Reiss, 2013), scenario analysis (Bañuls & Salmeron, 2007; Bañuls & Turoff 2011; Medina et al., 2015), and strategic management (Alizadeh et al., 2016).

Based on the adjacency matrix for weighted directed graphs, Wasserman and Faust (1994) investigated social networks. Following the so-called “sociomatrices” of Wasserman and Faust (1994), Ho & Chiu (2013) filtered more than 20,000 patents and created a network of patent activities and knowledge flows among 30 semiconductor companies. Caraiani (2013) derived a complex network based on a Granger causality matrix of relationships between countries, allowing them to characterize international business cycles. Joseph et al. (2014) applied a so-called multiple linear regression (MLR)-fit network (MLR combined with big data and network science) to model global economic interactions, providing an accurate phenomenological description with high predictive power despite the large number of possible interaction channels. Global foreign direct investment networks were analyzed by Bolívar et al. (2019), who prepared a directed network matrix covering 229 countries for each year.

The cross-impact approach has been applied in project management to contribute to stakeholder management for mega projects (Frahm & Rahebi, 2021) and to model all project stakeholders and their relationships (Reiss, 2013). Scenario analysis has been used to assess national technology policies (Bañuls & Salmeron, 2007; Bañuls & Turoff 2011), identify the barriers that influence decisions to invest in solar power (Medina et al., 2015), and develop more resilient conservation policies in the energy industries (Alizadeh et al., 2016).

Other diverse applications relate to the investigation of sustainable development strategies using the sensitivity model (Chan & Huang, 2004; Huang et al., 2009), the combination of cross-impact analyses with patent analyses to estimate technological impacts based on multiple patent classifications (Choi et al., 2007), the analysis of the potential for telemedicine (Gausemeier et al., 2012), as well as the development and analysis of key performance indicators for organizational structures in construction, real estate management (Zimmermann & Eber, 2014), and production (Köchling et al., 2018). Dubey and Ali (2014) employed a fuzzy cross-impact analysis approach to identify flexible manufacturing system dimensions and their interrelationships. Asan et al. (2004) presented a qualitative cross-impact analysis in terms of fuzzy relationships. The analytic hierarchy process (AHP) decision model has been combined with cross-impact analysis as a technological forecasting approach by Cho and Kwon (2004) and Saaty (2004). Barati et al. (2019) presented an integrated method that combines AHP techniques with cross-impact analysis to identify important strategic factors in agriculture.

In most of the papers on the cross-impact approach, the direct impact matrix is used to determine *AS* and *PS*. Relatively few authors have addressed powered impact matrices (Arcade et al., 1999; Jodlbauer, 2020; Zimmermann & Eber, 2014). The direct impact matrix shows the direct pairwise impact between two variables V_i and V_j. In comparison, the squared impact matrix shows the indirect impact of variable V_i on variable V_j via exactly one intermediate variable. The squared impact matrix refers to all indirect connections with path length two i.e., one intermediate variable (node). Generally, the $k-th$ power of the impact matrix describes the indirect pairwise impact between the variables via all possible paths with length k, i.e., $k-1$ intermediate variables. For illustration, the squared impact matrix is shown for the simple example mentioned above (see Table 2):

$$A=\begin{pmatrix}0&1&3&0\\2&0&1&2\\2&3&0&3\\3&0&1&0\end{pmatrix}, A^2=\begin{pmatrix}8&9&1&11\\8&5&8&3\\15&2&12&6\\2&6&9&3\end{pmatrix} \tag{7}$$

Godet (1987) introduced the MICMAC (Impact Matrix Cross-Reference Multiplication Applied to a Classification: Matrices d’Impacts Croises—Multiplication Appliqué un Classement) method to analyze the indirect relationships and diffusion of impacts through paths and loops involving intermediate variables. Godet defined both the influence and the dependence rank. The influence rank is based on the *AS* value (row sum) of the impact matrix. The variable with the highest *AS* has influence rank 1, the variable with the second-highest *AS* has influence rank 2, and so on. The dependence rank is based on the *PS* value (column sum). The variable with the highest *PS* is assigned dependence rank 1, and so on. Indirect classification is obtained by increasing the power of the impact matrix and determining the row and column sums of the powered matrices. According to Coates and Godet (1994), the classification, especially the rank order, generally becomes stable for power degrees higher than 5. Our research contribution builds on precisely this point, first, by identifying counter examples, second, by demonstrating analytically that there are cases in which no stable state exists, and third, by deriving an analytical categorization of the direct impact matrix that leads to stable rank orders. Linss and Fried (2010) presented an advanced impact analysis technique for processing data from cross-impact analyses considering both direct and indirect impacts. They examined manually calculated matrix multiplications and then evaluated the stability of sequences of active or passive sums. Gräßler et al. (2019) modeled the indirect impacts by applying the page-rank algorithm (Page et al., 1999) to the corresponding adjacency matrix. The determined page-ranks are then applied instead of the aforementioned influence ranks when using powered impact matrices. The dependency rank is determined by the page-rank of the transposed impact matrix.

Table 2: Squared impact matrix with active sum, passive sum, P -values, and Q -values.

	V1	V2	V3	V4	AS	P
V1	8	9	1	11	29	957
V2	8	5	8	3	24	528
V3	15	2	12	6	35	1050
V4	2	6	9	3	20	460
PS	33	22	30	23		
Q	0.88	1.09	1.17	0.87		

For a time-discrete Markov chain (Norris, 1998), the transition matrix A_{Markov} describes the transition probability from one state to another. A Markov transition matrix has some similarities to the impact matrix introduced by Gordon and Hayward (1968), but also some structurally different characteristics:

$$A_{Markov} = \left(a_{i,j}\right)_{i=1,\dots,n}^{j=1,\dots,n} \in [0,1]_n^n$$

and

$$\sum_{i=1}^{n} a_{i,j} = 1 \text{ for all j} = 1, \dots, n \tag{8}$$

The column sum (*PS*) for a Markov transition matrix has to be equal to one for every column, and the diagonal elements are not necessarily equal to zero. Under certain assumptions, a Markov chain is stable and converges to the unique invariant distribution p :

$$\lim_{k\to\infty} A_{Markov}^{k}\, p_o = p$$

$$\text{for every arbitrary initial state } p_0 \tag{9}$$

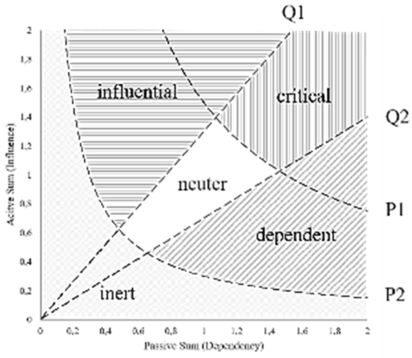

Figure 4: Influence-dependency chart and categorization regions.

One of the main objectives of this paper is to investigate the direct impact matrices for which the total impact matrix is stable and convergent in the sense of converging rank orders of *P*-values and *Q*-values.

The research questions addressed in this article are:

(i) How are variables ranked or how do their roles change when total impact matrices are used instead of the corresponding direct impact matrices? To answer this question, we perform comparisons between the direct impact matrix and the total impact matrix (sum of direct and all indirect impacts) of matrices of different orders to identify changes in the drivers and outcomes (influence–dependence).

(ii) How do transitive relations affect the ranking of variables? To answer this question, the influence of transitive relations on the total impact matrices compared to their direct impact matrices is analyzed.

(iii) What are the implications of applying the total impact matrix for managerial decision-making?

Jodlbauer et al. (2021) discussed the conditions under which normalization occurs, i.e., the Q -value and the rank orders of the powered impact matrices converge to a stable state. Furthermore, the rank orders of P -values, *AS*, and *PS* converge to a stable state. In the case of convergence, the stable state matrix should be used to determine the *AS*, *PS*, Q -values, and P -values, and the influence–dependency chart for their visualization.

The remainder of this article is organized as follows. Section 2 provides a brief introduction to the DEMATEL approach. For impact matrices, the DEMATEL model is applied to determine the total impact matrix, which reflects all possible direct and indirect impacts between all variables, and to prepare an influence–dependency chart and categorize the variables. In section 3, numerical analysis is conducted to identify the possible differences that occur when using the direct impact matrix or the total impact matrix. Finally, section 4 discusses the implications of the proposed model for research and management and identifies the limitations of this study, and presents some ideas for future research.

2 INDIRECT IMPACT MODEL (TOTAL IMPACT MATRIX)

We briefly describe the determination of the total impact matrix using the classical DEMATEL approach (Gabus & Fontela, 1972), the visualization of the influence–dependency chart, and the categorization of variables. Let $A = \left(a_{i,j}\right)_{i=1,\dots,n}^{j=1,\dots,n} \in \mathbb{R}_n^n$ be a direct impact square matrix with real nonnegative entries $a_{i,j} \geq 0$ and $a_{i,i} = 0$. The first step is the normalization of the direct impact matrix, which is defined as:

$$D = \frac{1}{s} A \quad (10)$$

where s is defined as follows:

$$s = max\left(\max_{1\leq i\leq n} \sum_{j=1}^{n} a_{i,j}, \max_{1\leq j\leq n} \sum_{i=1}^{n} a_{i,j}\right) \quad (11)$$
$$D = \left(d_{i,j}\right)_{i=1,\dots,n}^{j=1,\dots,n} \in \mathbb{R}_n^n, \text{ and } 0 \leq d_{i,j} \leq 1.$$

The total impact matrix is obtained by adding all direct and indirect impacts:

$$T = \lim_{k\to\infty} \sum_{i=1}^{k} D^i,$$

assuming that a limit exists, we have:

$$T = \lim_{k\to\infty} D \sum_{i=0}^{k-1} D^i = \lim_{k\to\infty} D\left(I-D\right)^{-1}\left(I-D\right)\sum_{i=0}^{k-1} D^i \quad (12)$$
$$T = D\left(I-D\right)^{-1} \lim_{k\to\infty}\left(I-D^k\right) = D\left(I-D\right)^{-1}$$

The final total impact matrix is:

$$T = D\left(I-D\right)^{-1}$$

The matrix $T = \left(t_{i,j}\right)_{i=1,\dots,n}^{j=1,\dots,n}$ reflects all direct and indirect impacts and is called the total impact matrix; this is the sum of all powered normalized impact matrices. To visualize the stable impact state and categorize the variables, the AS, PS, P-values, and Q-values are determined for the stable state matrix T and the influence–dependency chart is utilized for matrix T (see Figure 4).

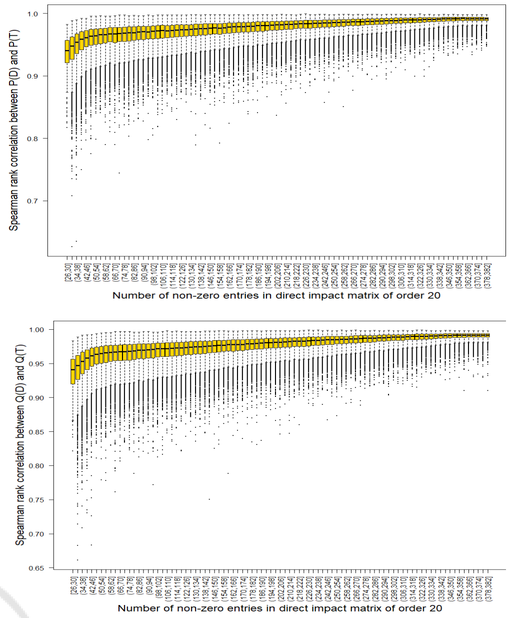

Figure 5: Spearman rank correlation $r_S\left(P(A), P(T)\right)$ and $r_S\left(Q(A), Q(T)\right)$ between P-values and Q-values with respect to the number of non-zero entries of randomly generated matrices.

$$\begin{aligned}
AS_i &= \sum_{k=1}^{n} t_{i,k} && i^{th} \text{ active sum} \\
& && (\text{sum of the } i^{th} \text{ row of the matrix } T) \\
PS_j &= \sum_{k=1}^{n} t_{k,j} && j^{th} \text{ passive sum} \\
& && (\text{sum of the } j^{th} \text{ column of the matrix } T) \\
Q_i &= \frac{AS_i}{PS_i} && i^{th}\ Q\text{-value} \\
& && (\text{quotient active sum over passive sum}) \\
P_i &= AS_i PS_i && i^{th}\ P\text{-value} \\
& && (\text{product active sum by passive sum})
\end{aligned} \quad (13)$$

The AS, PS, P-values, and Q-values are used to construct the influence–dependency chart shown in Figure 4. The x-axis of the influence–dependency chart reflects the PS values and the y-axis reflects the AS values. We define ISO-P-curves, $AS_{ISO-P}(PS)$, and ISO-Q-curves, $AS_{ISO-Q}(PS)$, as functions of PS as follows:

$$AS_{ISO-P}(PS) = \frac{P}{PS}$$
$$AS_{ISO-Q}(PS) = Q\ PS \quad (14)$$

An ISO-P-curve for a fixed P-value is a decreasing function containing all pairs (PS, AS) that have the same P-value. The ISO-P-curve for a fixed P-value consists of all pairs that have the same relevance P for the system. An ISO-Q-curve for a fixed Q -value is an increasing function of pairs (PS, AS) that have the same power Q to influence the system or to be controlled by the system. On the 45° line where $AS_{ISO-Q}(PS) = PS$, there is an equilibrium between influential and dependent categories.

For the five categories addressed in Figure 4—critical, influential, dependent, neuter, and inert—we propose the following definitions:

$$\begin{aligned}
&(PS, AS) \text{ with:} \\
&P = PS\ AS \\
&\text{and,} \\
&Q = \frac{AS}{PS} \text{ belong to} \qquad (15) \\
&\text{critical} \Leftrightarrow Q2 \le Q \le Q1 \text{ and } P \ge P1 \\
&\text{influential} \Leftrightarrow Q > Q1 \text{ and } P \ge P2 \\
&\text{dependent} \Leftrightarrow Q < Q2 \text{ and } P \ge P2 \\
&\text{neuter} \Leftrightarrow Q2 \le Q \le Q1 \text{ and } P2 \le P < P1 \\
&\text{inert} \Leftrightarrow P < P2
\end{aligned}$$

For practical reasons, the P-values $P1$ and $P2$ and the Q -values $Q1$ and $Q2$ can be chosen to ensure that the number of essential variables (critical, influential, and dependent) is manageable. Let $n_{critical}$ be the number of manageable critical variables, n_{Input} be the number of manageable influential variables (input), n_{Output} be the number of manageable dependent variables (output), and n_{inert} be the number of intended inert variables. For these values (n being the total number of variables and n_{neuter} being the total number of intended neuter variables), the following is true:

$$\begin{gathered}
n > 0, n_{critical} > 0, n_{Input} > 0, n_{Output} > 0, \\
n_{neuter} > 0, n_{inert} > 0 \\
n_{critical} + n_{Input} + n_{Output} + n_{neuter} + n_{inert} = n \\
Q2 < 1 < Q1, P2 < P1 \qquad (16)
\end{gathered}$$

To prioritize management activities, we propose the following setting to place the focus on the most important issues, that is, the management of key variables (i.e., critical, influential, and dependent variables). Fix $n_{critical}, n_{Input}, n_{Output}$ and n_{inert}, and use the following criteria:

(i) Choose $P2$: $\quad |\{(PS, AS) \in \Omega | PS\ AS < P2\}| = n_{inert}$

(ii) Choose $Q1$:

$$\left|(PS, AS) \in \Omega \left\{\left|\frac{AS}{PS} > Q1 \text{ and } PS\ AS \ge P2\right\}\right|\right. = n_{Input}$$

(iii)Choose $Q2$:

$$\left|(PS, AS) \in \Omega \left\{\left|\frac{AS}{PS} < Q2 \text{ and } PS\ AS \ge P2\right\}\right|\right. = n_{Output}$$

(iv) Choose $P1$:

$$\left|(PS, AS) \in \Omega \left\{\left|Q2 \le \frac{AS}{PS} \le Q1 \text{ and } PS\ AS \ge P1\right\}\right|\right. = n_{critical}$$

whereby,

$$\Omega = \{(PS_i, AS_i) | i = 1,2, \dots, n\} \qquad (17)$$

The output variables should be mainly used to monitor the system and the input variables should be used to control the system. If an input variable is mainly controlled by external stakeholders, there is a high risk that the system is not manageable. The critical variables require the greatest attention from management, who must monitor and control all critical variables.

3 NUMERICAL ANALYSIS

Numerical analyses of randomly generated direct impact matrices are now presented to illustrate the importance of the total impact matrix T and its comparison with the direct impact matrix A. For the analysis, the following tasks must be performed:

1. Generate random direct impact matrices A of order n (variables) by varying nonzero entries of A such that the row sum and column sum of each variable are greater than zero. We generate direct impact matrices of order $n = 20,30,40,50,60,80$ and 100 with different proportions of nonzero entries varying from $0.05, 0.1, 0.15, \dots, 1$ to analyze the effect of higher-order matrices and transitive relations of the total impact matrix. For random matrix generation, we start with a null matrix A of order n, and assign nonzero entries (direct impacts) sampled uniformly from $\{1,2,3\}$ to m nondiagonal entries of A ($m \ge n$, and $m \le n^2 - n$).
2. Compare the influence–dependence measures between direct impact matrices A and corresponding total impact matrices T. Calculate the influence–dependence measures (AS, PS, P, and Q) and compare the P -values and Q -values between matrices A and T by computing the Spearman rank correlation (Spearman, 1904) to show the differences between the ranks of variables with respect to the number of nonzero entries in matrix A.
3. Compute the proportion of variables that change from influential to dependent and vice versa by

examining $Q(A)$ and $Q(T)$ values of variables considering different values for $Q1$ and $Q2$ (see Figure 4).

4. Determine the impact of the transitive relations of variables on the total impact matrix.

For the numerical analysis, ~600,000 random matrices were generated by varying the number of nonzero entries in direct impact matrices of order n. Next, the matrices were analyzed to evaluate the rank difference of variables, where the ranks of variables were computed from the direct impact matrices A and corresponding total impact matrices T. The Spearman rank correlation $\left(r_S\big(P(A), P(T)\big), r_S\big(Q(A), Q(T)\big)\right)$ between the P-values and Q-values *of each direct impact matrix and corresponding total impact matrix was calculated* to summarize the rank difference of variables of randomly generated direct impact matrices. The results are shown in Figure 5. The x-axis is the number of nonzero entries in the randomly generated matrices. The y-axis is the Spearman rank correlation $\left(r_S\big(P(A), P(T)\big), r_S\big(Q(A), Q(T)\big)\right)$ of P-values and Q-values, summarizing the rank difference of variables. The Spearman rank correlation results show that the total impact matrices T provide different rankings of variables than the corresponding direct impact matrices A. The rank correlation variation is higher in sparse matrices than in dense matrices, indicating that the rank difference of variables is likely to be higher in sparser matrices. Next, the highest and lowest rank correlation of P -values and Q -values were computed (see Figure 5). The highest and lowest correlations for P are ~0.99 (when, for instance, matrix A has 228 nonzero entries) and 0.62 (when matrix A has 34 nonzero entries). The highest and lowest correlations for Q are ~0.99 (when, for instance, matrix A has 228 nonzero entries) and ~0.66 (when matrix A has 32 nonzero entries). The highest rank correlation values indicate that the ranking of variables has not changed significantly and the same rank is maintained in both matrices for P and Q. The lowest rank correlation values show that the ranking of variables obtained using the total impact matrix T has changed significantly. A significant change in ranking means that the influence–dependence effect of variables on each other calculated by the direct impact matrix A is significantly different from that given by the total impact matrix T. Further, the rank difference for matrices varies between the minimum and maximum values.

In other cases, variables may change from influential to dependent or from dependent to influential in the total impact matrix T compared with the direct impact matrix A, defined as a *role-change*. For this analysis, we calculated the proportion of *role-change* variables in the total impact matrix as follows. We selected different values for $Q1$ and $Q2$ as decision boundaries to determine whether $Q_i(A)$ and $Q_i(T)$ for the i^{th} variable are on the same side of the decision boundary (i.e., $Q_i(A) > Q1 \wedge Q_i(T) > Q1$ or $Q_i(A) < Q1 \wedge Q_i(T) < Q1$), which defines the influence or dependence effect of the variable. The selected decision boundaries $Q1$ and $Q2$ were {(1,1), (1.05, 0.95), (1.10, 0.90), (1.15, 0.85), (1.20, 0.80), (1.25, 0.75)}. If a variable does not lie on the same side of the decision boundary for both the direct impact matrix and total impact matrix, then the role of this variable as an influential or dependent variable is different in the total impact matrix than in the direct impact matrix. The proportion was calculated as follows:

$$prp(D,T) = \frac{\sum_{i=1}^{n} I\Big(\big(Q_i(A) < Q_2 \wedge Q_i(T) > Q_1\big) \vee \big(Q_i(A) > Q_1 \wedge Q_i(T) < Q_2\big)\Big)}{n} \quad (18)$$

where $I(.)$ is an indicator function that returns 1 if the input is true and 0 otherwise; n is the order of the matrix. We further estimated the percentage of matrices that have *role-change* variables when using the total impact matrix compared with the direct impact matrix for randomly generated matrices of order $n = 20{,}30{,}40{,}50{,}60{,}80$ and 100. The results are presented in Table 3. The first column is the interval of the percentage of *role-change* variables in a total impact matrix (T) compared with a direct impact matrix (A). The other columns show the percentages of randomly generated matrices in corresponding *role-change* intervals for different boundaries of $Q1$ and $Q2$. The *role-change* categories of variables are divided into four intervals to better understand the likelihood of matrices that have *no change*, *small change*, *medium change*, or *large change* in the influence–dependence groups of variables in T compared with A. The four intervals are: 1) *no change*, i.e., equal to zero, 2) *small change*, i.e., (0,5]% of variables change role, 3) *medium change*, i.e., (5,10]% of variables change role, and 4) *large change,* i.e., >10% of variables change role.

Table 3: Percentage of randomly generated matrices in different role-change intervals in their total impact matrix T compared to direct impact matrix A.

Percentage change of variable's influence-dependence group in T compared to A (grouped into Intervals)		Percentage of randomly generated matrices of order, n=20.					
Interval type	Interval	Q1=Q2=1	Q1=1.05, Q2=0.95	Q1=1.10, Q2=0.90	Q1=1.15, Q2=0.85	Q1=1.20, Q2=0.80	Q1=1.25, Q2=0.75
No change	=0	66.4	88.3	95.3	97.9	99.1	99.7
Small change	(0,5]	25.8	10	4.3	2	0.9	0.3
Medium change	(5,10]	6.4	1.5	0.4	0.1	0	0
Large change	>10	1.3	0.2	0	0	0	0
		Percentage of randomly generated matrices of order, n=30.					
No change	=0	57.1	88.6	95.9	98.3	99.3	99.7
Small change	(0,5]	29.1	9.1	3.6	1.6	0.7	0.3
Medium change	(5,10]	13.1	2.2	0.5	0.1	0	0
Large change	>10	0.7	0	0	0	0	0
		Percentage of randomly generated matrices of order, n=40.					
No change	=0	50.1	89.5	96.4	98.5	99.3	99.7
Small change	(0,5]	43.8	10	3.5	1.5	0.7	0.3
Medium change	(5,10]	5.8	0.5	0.1	0	0	0
Large change	>10	0.3	0	0	0	0	0
		Percentage of randomly generated matrices of order, n=50.					
No change	=0	45.1	90.4	96.9	98.6	99.3	99.7
Small change	(0,5]	45.9	9	3	1.4	0.7	0.3
Medium change	(5,10]	8.8	0.6	0.1	0	0	0
Large change	>10	0.2	0	0	0	0	0
		Percentage of randomly generated matrices of order, n=60.					
No change	=0	41.1	91.2	97.3	98.7	99.3	99.7
Small change	(0,5]	54.7	8.6	2.7	1.3	0.7	0.3
Medium change	(5,10]	4.1	0.2	0	0	0	0
Large change	>10	0.1	0	0	0	0	0
		Percentage of randomly generated matrices of order, n=80.					
No change	=0	35.1	92.7	97.6	98.6	99.2	99.7
Small change	(0,5]	62	7.3	2.4	1.4	0.8	0.3
Medium change	(5,10]	2.8	0	0	0	0	0
Large change	>10	0	0	0	0	0	0
		Percentage of randomly generated matrices of order, n=100.					
No change	=0	31	93.9	97.7	98.5	99.2	99.7
Small change	(0,5]	67	6.1	2.3	1.5	0.8	0.3
Medium change	(5,10]	2	0	0	0	0	0
Large change	>10	0	0	0	0	0	0

In Table 3, as the matrix order increases, the percentage of matrices in the *no change* category decreases for the cases where $Q1 = Q2 = 1$. In addition, a significant percentage of matrices show a *small change*, the percentage of matrices that show a *medium change* varies from ~6.4% to 2%, and fewer than 1% of matrices fall into the *large change* category. As the width between decision boundaries $Q1$ and $Q2$ increases, the percentage of matrices in the *no change* category increases from 80% to 99.7%. Matrices gradually fall into the *no change* category as the width between $Q1$ and $Q2$ increases, with only a small fraction exhibiting *small* or *medium change*. The percentage of matrices in the *small change* and *medium change* categories decreases from 11.7% to 0.3% for different values of $Q1$ and $Q2$ (in increasing order), and for different orders (n) of matrices. However, we did not consider the change in neuter variables to influence–dependence groups. This analysis provides two important insights. First, it highlights the importance of the total impact matrix, as we observe that the matrices fall into the categories of *small*, *medium*, and *large change*. Second, we can see the importance of the selection of decision boundaries $Q1$ and $Q2$. The user must select valid impact boundary criteria under the supervision of domain experts to determine $Q1$ and $Q2$; otherwise, the indirect impact model will produce ineffective results.

Next, the percentages of matrices in the four different *role-change* categories based on the proportion of nonzero entries in random direct impact matrices of different orders were calculated. The results are shown in Figure 6. More than 50% of the sparser matrices (proportion of nonzero entries of 0.05–0.25) show a *small*, *medium*, or *large change* in the influence–dependence groups of variables when $Q1 = Q2 = 1$ for different orders of matrices (see Figure 6). As the matrices become dense, the rank order difference decreases gradually, and the percentages of matrices showing a *small change* in influence–dependence groups of variables increase. As the width increases between $Q1$ and $Q2$, the *small*, *medium*, and *large change* categories disappear, and a small fraction of the matrices remain in the *small* and *medium change* categories.

It is important to note that the *small change* (0,0.05] (interval (only some variables change role), in which a significant percentage of matrices are grouped (depending on the width between $Q1$ and $Q2$), is not trivial and should not be ignored. Domain experts should assess the overall impact of these few variables. Even if the number of variables that change their group orders is small, the overall impact can be large depending on the type of problem that is addressed. Nevertheless, the change may be *large* or *small*, which underscores the importance of a total impact matrix from which influence–dependence ranks can be calculated to measure the direct and indirect impact of the variables. In this numerical analysis, categorizing the variables that change groups into these four categories highlights the importance of the total impact matrix T for measuring the indirect impacts of the variables on each other.

Finally, we examined the effect of transitive relations on the proportion of variables that changed influence–dependence groups (*role-change*) in T. We searched for transitive relations using a weighted transitive measure. A weighted transitive relation in the direct impact matrix is defined as follows: in a direct impact matrix, a triplet (i, j, k) is transitive, where $\{(i, j), (j, k), (i, k)\}$ is a set of ordered pairs defining the relations between the i^{th}, j^{th} and k^{th} variables, if the impact $a_{i,k} \geq min(a_{i,j}, a_{j,k})$ given that $a_{i,j}, a_{j,k} > 0$. We applied the social network analysis package *sna* (Butts, 2008) to calculate the transitive measure for a randomly generated direct impact matrix. The transitive measure is the fraction of transitive relations for which $a_{i,k} \geq min(a_{i,j}, a_{j,k})$ (Wasserman & Faust, 1994):

$$\mathrm{trn(A)} = \frac{\sum_{i=1}^{n}\sum_{\substack{j=1\\ j\neq i}}^{n}\sum_{\substack{k=1\\ k\neq i\\ k\neq j}}^{n} I\left(a_{i,k} \geq \min\left(a_{i,j}, a_{j,k}\right) \wedge a_{i,j} \neq 0 \wedge a_{j,k} \neq 0\right)}{\sum_{i=1}^{n}\sum_{\substack{j=1\\ j\neq i}}^{n}\sum_{\substack{k=1\\ k\neq i\\ k\neq j}}^{n} I\left(a_{i,j} \neq 0 \wedge a_{j,k} \neq 0\right)} \quad (19)$$

The main objective of this analysis is to understand whether changing the role of the variables in the influence–dependence group in T produces a systematic effect as the order of the matrices and the number of transitive relationships change. A second reason for this analysis is to understand the importance of assigning impacts between variables with transitive relations. The results of the average change in proportion of variables with respect to the transitivity measure (divided into different intervals in increasing order) are shown in Figure 7 for matrices of different orders and with different decision boundaries $Q1$ and $Q2$. The results for $Q1 = Q2 = 1$ show that an average of ~2.5% of variables change their role in the influence–dependence group in T when no or a small number of transitive relations are observed. This value decreases gradually as the number of transitive relations increases. When the decision boundary threshold for $Q1$ and $Q2$ is changed, the expected proportion of variables that change the influence–dependence group in T decreases and the expected proportion is insignificant. This trend remains similar for matrices

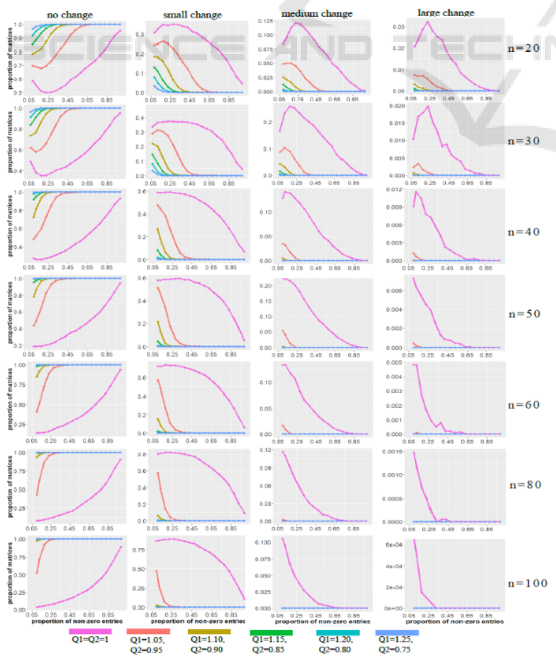

Figure 6: Proportion of randomly generated matrices in different role-change intervals with respect to the proportion of non-zero entries in the randomly generated matrices.

of different orders; however, there is a slight decrease (downward shift) in the average proportion change of variables as the order of the matrices increases, indicating that the average percentage change in each variable becomes smaller. The expected change approaches zero in denser matrices (where the number of transitive relations is higher) for all matrix orders. The complexity of the relations between variables (defined as the impact) may result in the variables being grouped into different categories so as not to ignore indirect impacts when using a direct impact matrix for complex decision-making in a business scenario. However, the total impact matrix may be ineffective and redundant if impacts are added arbitrarily without proper consideration, or if the $Q1$ and $Q2$ boundaries are not carefully selected. Otherwise, the results could lead to inaccuracies and produce an ineffective impact matrix, resulting in incorrect calculations.

4 DISCUSSION AND CONCLUSION

4.1 Research Implications

The following research implications arise from this study. First, when the direct impact matrix A is very sparse (i.e., contains few impacts), there is a high risk that using direct impact matrix analysis to identify influence–dependence variables will produce incorrect results. Second, the numerical analysis shows that the rank orders, importance, or category of variables can change significantly between the direct impact matrix A and the total impact matrix T.

We observe two types of changes. First, a rank change, where the role of the variables remains the same. Second, a change in the influence–dependence groups in the total impact matrix. Both types lead to different interpretations of the system and variables when using the total impact matrix T. The proportion of influence–dependence variables in the total impact matrix T is significantly different for sparser matrices. This affects whether decisions should be made based on matrix A or matrix T. A greater number of transitive relations (high transitive score) in the direct impact matrix A will result in a smaller difference in the rank orders of variables between matrix A and matrix T, and so T does not provide any significant results. When matrix A is sparse, the difference in rank orders is greater.

In managerial applications, a higher number of transitive relations may indicate one of three things, assuming that for variables i, j, and k, $a_{j,k} \geq min(a_{i,j}, a_{j,k})$ holds (as discussed in section 3): 1) A direct impact with an in-depth domain understanding; 2) Inaccurate/arbitrarily assigned impacts; 3) A relation derived by estimating indirect impacts. In the second and third cases, the results of the total impact matrix are useless or incorrect. It may seem that the indirect relations are known, a direct impact matrix analysis may be applicable, or a denser random relation may lead to ineffective results. It is important not to introduce impacts randomly and not to assign indirect relations by establishing direct relations between variables. Our analysis emphasizes that indirect impacts should be computed for managerial applications, assigning only direct impacts (using an appropriate evaluation criterion) to construct an initial direct impact matrix, and using a statistically valid criterion with an appropriate domain understanding for $Q1$ and $Q2$.

4.2 Managerial Implications

Systems that are difficult to understand and interpret pose a strategic challenge to decision makers and stakeholders. In decision making, for example, at the top management level of a multinational company, decision makers deal with systems that are difficult to oversee and contain pairwise impacts of direct as well as indirect variables. Our method makes the indirect impact of variables visible and manageable: The presented study can contribute to an improved visualization (see influence-dependency chart of matrix T) as well as to a better understanding of total impact matrices compared to the use of direct impact matrices, thus supporting consensus building among decision makers and helping management in strategic planning and decision-making processes (e.g., implementing targeted, well-coordinated actions). Key variables can be identified and visualized in the influence-dependency chart. The decision boundaries in the influence-dependency chart should be selected carefully so that the overall impact of the variables is not over- or underestimated. In addition, management can use the chart to determine whether variables in the system are critical variables (and should thus be treated with the greatest attention) or not. KPIs can be derived from dependent output variables and support management in decision-making.

The following recommendation can be made to managers: The insight of a cross-impact analysis conducted with the DEMATEL approach is that significant differences between a direct impact matrix and a total impact matrix are possible. However, there might be cases where the ranking of variables does not change when proportion of non-zero entries are higher. This may be due to an arbitrary selection of relations resulting in a high proportion of non-zero relations, or unassessed transitive relations. If the experts correctly assess the transitive relations, this will not affect the interpretation of the results, but random or incorrect assessment of the relations would lead to misinterpretation and potentially provide ineffective or redundant results. Therefore, managers are recommended to always work with matrix T when estimating the overall impact of variables on each other, as the variables may have a different categorization compared to the direct impact matrix A. In contrast to matrix A, the total impact matrix T also contains all indirect relationships between the variables. The potential applications of the model are diverse and extend far beyond the management level. Especially in international business, when global production networks, international operations networks, networks of foreign suppliers, global FDI networks, or global R&D networks are concerned, the method can support decision makers in complex decisions. Further application examples are business model innovation, urban development, politics, or risk analysis.

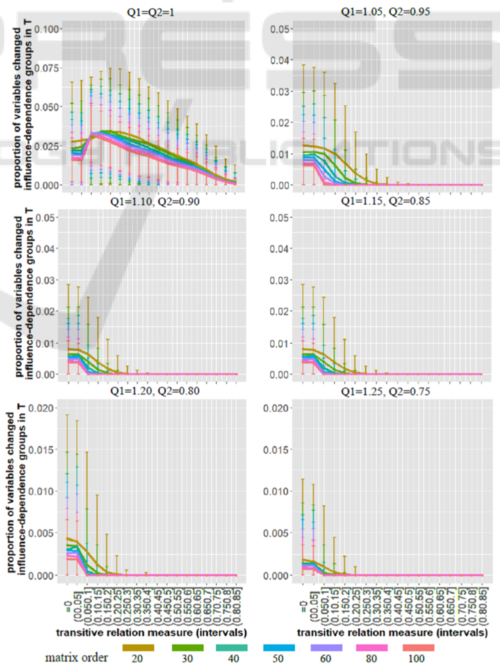

Figure 7: Average proportion of variables changed.

4.3 Future Research and Limitations

In future research, the presented DEMATEL model should be applied to pilot projects, case studies, and empirical studies, taking into account the complexity of the system's transitive, modular, or hierarchical relationships. The presented approach is applicable in practical environments (e.g., production, quality control, process optimization, business model innovation) and not only in randomly generated situations. One limitation of this study is that the model has been exclusively applied to positive matrices with the coding $\{1,2,3\}$. In the future, it is recommended that investigations examine whether the model can be applied to matrices with other codings that allow negative values. A key challenge to overcome is the definition of impacts between variables, especially in transitive cases. For example, in developing a direct impact matrix, different experts may assign different impacts, leading to cases of transitivity where indirect and direct impacts exist between variables and the weights of the sums of indirect and direct relations are different. Such cases need to be investigated using cross-impact analysis matrices that account for direct and indirect impacts. Another challenge involves validating the impact of variables in practical situations (allowing valid interpretation by domain experts) using cross-impact analysis matrices that consider direct and indirect impacts of realistic business scenarios.

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