



MSDO / MDSO: A TECHNIQUE FOR REDUCING THE NUMBER OF CAUSAL CONDITIONS IN QUALITATIVE COMPARATIVE ANALYSIS

MSDO/MDSO: UMA TÉCNICA PARA A REDUÇÃO DO NÚMERO DE CONDIÇÕES CAUSAIS NA ANÁLISE QUALITATIVA COMPARATIVA

MSDO/MDSO: UNA TÉCNICA PARA REDUCIR EL NÚMERO DE CONDICIONES CAUSALES EN EL ANÁLISIS COMPARATIVO CUALITATIVO

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ABSTRACT

Objective: this paper aims to exemplify and analyze each of the operational steps of the MSDO / MDSO technique in order to reduce the systemic complexity in the use of the csQCA method, with the support of the MSDO / MDSO web application.

Methodological Design: Comparative analysis: more different cases with equal results and more similar cases with different results (MDSO / MSDO). An application of the technique was carried out to identify the causal conditions that explain the differences in innovative performance in 26 innovation networks in Brazil and Spain.

Results From the twenty causal conditions analyzed, which were grouped into four categories (clusters) called Structural, Human, Financial and Organizational Resources, eight causal conditions explaining the difference in performance were identified.

Methodological implications: Considering that one of the main problems in social research, including recent innovation studies, is the size of systemic complexity. The difficulty of reducing systemic complexity has been manifested repeatedly when researchers in the field of Administration and Innovation have used case analysis with binary data, called Crisp Set Comparative Qualitative Analyzes - csQCA. The MSDO / MDSO analysis (more different cases with equal results and more similar cases with different results) contributed to minimize this problem

Originality: the technique has been less used in Brazil. The four stages of application of the technique are detailed demonstrated and analyzed.

Keywords: Crisp Set QCA. Comparative Qualitative Analysis. Causal Conditions Reduction.

RESUMO

Objetivo: este artigo tem o objetivo de exemplificar e analisar cada uma das etapas operacionais da técnica MSDO/MDSO com vistas à redução da complexidade sistêmica no uso do método csQCA, com o apoio do *software* MSDO / MDSO.

Design / metodologia / abordagem: Análise comparativa: casos mais similares com diferentes resultados/ casos mais diferentes com o mesmo resultado - MDSO / MSDO. Aplicação da técnica para a identificação das condições causais explicativas das diferenças de desempenho inovador em 26 redes de inovação do Brasil e da Espanha.

Resultados: Das vinte condições causais analisadas, as quais estavam agrupadas em quatro categorias (*clusters*) denominadas de Recursos Físicos, Humanos, Financeiros e Organizacionais foram identificadas 8 condições causais explicativas da diferença de desempenho.

Implicações metodológicas: Um dos problemas principais na pesquisa social, inclusive em recentes estudos de inovação, é o tamanho da complexidade sistêmica. A dificuldade de reduzir a complexidade sistêmica tem se manifestado reiteradamente quando os pesquisadores do campo da Administração e da Inovação tem se utilizado da análise de casos com dados binários, denominado de *Crisp Set Comparative Qualitative Analysis* – csQCA. A análise MSDO/MDSO (casos mais diferentes com resultados iguais e casos mais similares com diferentes resultados) contribuiu para minimizar esse problema.

Originalidade / valor: Técnica tem sido pouco utilizada no Brasil. As quatro etapas da aplicação da técnica são detalhadamente demonstradas e analisadas.

Palavras-chave: Inovação. Análise Qualitativa Comparativa. Redução da complexidade.

RESUMEN

Objetivo: este artículo tiene como objetivo ejemplificar y analizar cada uno de los pasos operativos de la técnica MSDO/ MDSO con el objetivo de reducir la complejidad sistémica en el uso del método csQCA, mediante el apoyo del MSDO/MDSO aplicación web.

Procedimientos Metodológicos: análisis comparativo: más diferentes casos con resultados iguales y más similares casos con resultados diferentes (MSDO / MDSO). Se realizó una aplicación de la técnica para identificar las condiciones causales que explican las diferencias en el desempeño innovador en 26 redes de innovación de Brasil y España

Resultados: de las veinte condiciones causales que se agruparon en cuatro categorías (*clusters*), denominadas Recursos Físicos, Humanos, Financieros y Organizacionales, se identificaron 8 condiciones causales que explican la diferencia de desempeño.

Implicaciones metodológicas: Uno de los principales problemas en la investigación social, en particular en los estudios recientes de innovación, es el tamaño de la complejidad sistémica. La dificultad para reducir la complejidad sistémica se

presenta frecuentemente cuando los investigadores del campo de la Administración y la Innovación emplean el análisis de casos con datos binarios, denominado Crisp Set Comparative Qualitative Analyzes - csQCA. El análisis MSDO/MDSO (más casos diferentes con resultados iguales y casos más similares con resultados diferentes) puede ayudar a minimizar este problema.

Originalidad: la técnica ha sido poco utilizada en Brasil. Las cuatro etapas de aplicación de la técnica son demostradas y analizadas.

Palabras-clave: Crisp Set QCA. Comparative Qualitative Analyzes. Reducción de la complejidad.

1. INTRODUCTION

The presence of many explanatory conditions for a phenomenon under investigation, together with a small number of cases researched, is a common situation encountered by many social researchers (De Meur & Gottcheiner, 2009; Pattyn, 2015). In order to make these studies more conclusive, one solution would be to reduce the number of explanatory conditions. However, establishing a scientific procedure to select which of these variables is imperative to the phenomenon under investigation is common problem encountered by researchers in the field of administration, and especially, innovation. This situation becomes even more common when using case analysis with binary data, a research approach known as Crisp-Set Qualitative Comparative Analysis (csQCA) (Dias, 2013; Dias, 2015; Dias & Pedrozo, 2015; Dias, Dias & Martín-Fernández, 2018). In this case, the MDSO/MSDO procedure (most similar different outcome/most different same outcome) could help to minimize this problem.

MDSO/MSDO analysis is a procedure used in comparative research, in which case analysis plays a central role (De Meur & Gottcheiner, 2009). The technique was developed by De Meur (1996) and, according to Pattyn (2015), it is a systematic application of the comparative research design in the field of social sciences proposed by Mill (1973). In the MDSO/MSDO analysis, the case is understood as a whole and described as a set of conditions. According to this definition, a difference between two cases could indicate a qualitative difference (a difference in kind) and not simply a difference in degree (Ragin & Sonnett, 2005; De Meur & Gottcheiner, 2009).

The MDSO/MSDO technique was developed in response to the following research questions: How to reduce systematic complexity without losing relevant information, and How to find the cases that will transmit information with explanatory value for the phenomenon under analysis through their comparisons. (De Meur & Gottcheiner, 2009). MDSO/MSDO is a comparative research technique indicated to solve these issues, even though it has still been little used (Pattyn, 2015), especially in Brazil.

This technique allows the researcher to compare different cases in a systematic and formal way, while maintaining the complexity of social phenomena (Pattyn, 2015). The MDSO/MSDO procedure is capable of detecting conditions with the potential to explain a phenomenon under analysis and is based on the comparison of pairs of cases in order to identify the conditions that might explain the differences in a result, by comparing more similar cases and identifying the conditions that can explain the similarity in the result through the comparison of more different cases (De Meur & Gottcheiner, 2009; Lucidarme, Cardon & Willem, 2016).

Thus, the MDSO/MSDO technique has been used as a preliminary or selection phase of the causal conditions to be considered in csQCA (De Meur & Gottcheiner, 2009). This is because the csQCA approach – to enable the analysis – needs a small set of causal conditions, especially when the number of cases is intermediate or small (less than 20 cases) (De Meur & Gottcheiner, 2009). Accordingly, the MDSO/MSDO technique helps us to select the causal conditions with explanatory value, without any pre-conceived ideas (De Meur & Gottcheiner, 2009). In addition, csQCA and MDSO/MSDO are based on Boolean algebra and involve the binary codification of cases in terms of conditions and results (Lucidarme, Cardon & Willem, 2016).

Considering that (i) the csQCA technique has been increasingly utilized in the field of administration and innovation, (ii) the need to reduce the systemic complexity to enable csQCA, and (iii) the limited use of MDSO/MSDO in the field of administration, the present research aims to exemplify and analyze each operational stage of the MSDO technique, in order to reduce the number of conditions for using the csQCA method. To perform these objectives, we utilized the MDSO/MSDO software, developed in 2015 by De Meur and Beumier (version 1.1; available via <https://www.jchr.be/01/v11.htm>) –.

To carry out the exemplification of the MDSO/MSDO method, we used the research data provided by Dias (2015), which utilized the csQCA method but not the MDSO/MSDO previously, thereby generating extensive solutions that were

difficult to explain and draw conclusions from. The study was conducted in Spain, where eight successful cases were analyzed, and in Brazil, where 18 cases were assessed – nine successful and nine unsuccessful. The causal conditions are represented by four clusters, totaling 20 causal conditions. Thus, this study represents a common problem faced by social researchers, which is the small number of surveyed cases (26 cases) and, proportionally, a high number of causal conditions (20 conditions). Since it is a study that exemplifies a method, the aim of our article is not to discuss theoretical foundations on the performance of networks, or to analyze the results of previous studies – such efforts have already been made by Dias (2015). The main contribution of our article is that it seeks to demonstrate each stage of the MDSO/MSDO method, with the aim of making the technique viable for future studies by researchers involved in the field of business administration.

Finally, to justify the exemplification of the method, it is necessary to provide a theoretical review of the stages of the MDSO/MSDO analysis, which will be demonstrated in Section 2. Section 3 describes and assesses each of the operational stages of the MDSO/MSDO technique based on the utilized data. Finally, Section 4 presents some final considerations about the contribution of the method to minimizing the number of causal conditions.

2. MDSO/MSDO ANALYSIS: Premises and stages

The MDSO/MSDO technique, developed by Gisèle De Meur (1996), is in fact a systematic application of the system of logic formulated by J.S. Mill (1843), which provides the basis for most comparative research projects in the social sciences (Pattyn 2015). However, instead of focusing on similar and different cases that may differ or share only one similar or different causal condition, MDSO/MSDO adopts a more realistic position, focusing on the pairs of most similar cases and most different cases (De Meur, 1996; De Meur & Beumier, 2015), with different or similar outcomes, respectively. The idea behind this method is that these (dis)similar cases may help to unravel the main explanatory factors of a phenomenon under analysis (Pattyn, 2015).

On the one hand, when a pair of cases is highly similar in many conditions, and yet present different outcomes, the researcher is supposed to comprehend the difference in the outcomes by investigating the differences of this limited set of causal conditions. On the other, when two cases are highly different and yet present the same outcome, then we must focus on their few similarities to understand their shared outcome. The differences and similarities, therefore, incorporate the greatest explanatory power, and these are the specific causal conditions on which the method is focused. The concept of case used in the method originates from the work of Ragin and Becker (1992). According to the authors, each case is considered as a separate and unique whole, which can be described as a set of innumerable causal conditions. These causal conditions are potentially different in nature.

Accordingly, the MDSO/MSDO analysis is based on Boolean data, where each causal condition needs to be dichotomized, i.e., converted to 1 or 0. The causal conditions and the outcome variable denoted 1 are understood as “present”, and the causal conditions denoted 0 are considered “absent”. The numbers 1 and 0 can also express a different qualitative status, such as “high” and “low”, respectively (Pattyn, 2015).

Each MDSO/MSDO analysis involves the following steps: 1) Measurement of similarities (MSDO) and differences (MDSO); 2) Determination of (dis)similarity levels; 3) Grouping similarity and difference levels; and 4) Identification of relevant causal conditions (De Meur, 1996; De Meur & Gottcheiner, 2009).

The first stage – measurement of similarities and differences – consists in identifying the most similar and most different pairs of cases. The first step is to create a dichotomized table. The dichotomized table supports distance calculations for cases presenting the same and different outcomes. For the calculation of distance, MDSO/MSDO relies on the Boolean distance measure; in other words, the distance is the absolute difference of the number of codified causal conditions (0-1) between two cases that differ from each other. This calculation is necessary for each condition in the categories (Pattyn, 2015).

After the computation of the Boolean distance for each case, it is possible to identify the minimum distance for pairs of cases with a different value on the outcome (MSDO) and the maximum distance for pairs with the same value on the outcome (MDSO) (De Meur, Bursens & Gottcheiner, 2006; De Meur & Gottcheiner, 2009; Pattyn, 2015).

The second stage – determining levels of (dis)similarity – consists in classifying the most similar and the most different pairs of cases. The most different pairs of cases are classified as Level 0 (D0). Level D1 is assigned to pairs whose sum of the differences is defined by $D0 - 1$ ($\sum D0 - 1$). The most similar cases are classified as Level 0 (S0). Level S1 is attributed to pairs whose sum of similarities is defined by $S0 + 1$ ($\sum S0 + 1$), and so on. The outcomes are presented in a distance matrix, which is composed of three different zones: Zone 1 represents the comparison between cases with the

same outcome, more precisely, the comparison between cases with outcome 1 (present). Zone 2 also represents the comparison between cases with the same outcome; more precisely, the comparison between cases with 0 (absent). Zone 3 indicates the comparison between cases with outcome 1 (present) and cases with outcome 0 (absent) (De Meur, Bursens & Gottcheiner, 2006; De Meur & Gottcheiner, 2009; Pattyn, 2015).

The third stage refers to the grouping of (dis)similarity levels. The Boolean distances of each pair of cases in a category must be compared to the distances of pairs in other categories. The aim of this stage is to create a combined view of the distances of the pairs in the set of categories (De Meur, Bursens & Gottcheiner, 2006; De Meur & Gottcheiner, 2009; Pattyn, 2015).

The fourth stage comprises the identification of the relevant causal conditions. Once the pairs of cases and categories are selected, it is possible to compare the pairs and identify which causal conditions matter the most, to explain the presence or absence of the outcomes (MDSO), and to identify which causal conditions are the most relevant to explain the difference between presence and absence (0-1) in the outcomes (MSDO) (De Meur, Bursens & Gottcheiner., 2006; De Meur & Gottcheiner, 2009; Pattyn, 2015).

Thus, in the fourth stage, it is also possible to identify the causal conditions that may support the similarities (MDSO) and differences (MSDO). However, the causal conditions stemming from the MSDO analysis are mostly used in very small samples, where the comparison of pairs may lead to a narrowing of the conditions such that it allows the identification of factors that may be responsible for the outcome (Berg-Schlösser & De Meur, 2009).

In Section 3, each of these stages will be exemplified through the presentation and analysis of partial and final results made available by the MDSO/MSDO software (version 1.1; available via <https://www.jchr.be/01/v11.htm>); the software was created by De Meur and Beumier in 2015.

3. MDSO/MSDO ANALYSIS IN RESEARCH NETWORKS IN BRAZIL AND SPAIN

The data analysis is based on the data collected by Dias (2015), who utilized the csQCA method, but without previously applying the MDSO/MSDO technique. The study by Dias (2015) was conducted in Spain, where eight successful cases were analyzed, and in Brazil, where 18 cases were analyzed (nine successful and nine unsuccessful). In that study, the analyzed cases were agricultural research programs in Brazil and Spain. Success and failure were considered as measures of performance (outcomes); these were represented by 1 (success) and 0 (failure).

The data collected consisted of a combination of sources, including primary and secondary data. The secondary data were obtained through documents, reports, and digital files provided by both institutions (Brazilian and Spanish) and public data banks. Subsequently, as a data collection technique for the Qualitative Comparative Analysis (QCA), online questionnaires were applied in the year 2015. The categories represented in the questionnaire were based on the literature, i.e., the different types of resources in research and development organizations. These theoretical categories depict the causal conditions represented by four clusters or categories of causal conditions (Dias, 2015):

- Physical resources of Category 1 subdivided into four causal conditions: Facilities (PhyR1), Equipment (PhyR2), Materials (PhyR3), and Service infrastructure (RFis4).
- Human resources of Category 2 subdivided into five causal conditions: R&D ability (HumR1), Management ability (HumR2), Commercial alignment (HumR3), Partnership ability (HumR4), and Learning (HumR5).
- Financial resources of Category 3 subdivided into four causal conditions: Funding institution within the maximum funding limit established by public calls [Inst_Limit (FinR1)], Funding institutions with much higher funding limits [Higher_Inst (FinR2)], Funding exclusively from external organizations (FinR3), and Funding from internal and external organizations (RFin4).
- Organizational resources of Category 4 subdivided into seven causal conditions: Intellectual property (OrgR1), Organizational structure (OrgR2), Processes (OrgR3), Image and Trademark (OrgR4), Organizational Culture (OrgR5), Market information (OrgR6), and Organizational strategy (OrgR7).

In order to define innovation performance for the Brazilian research networks (i.e., the Brazilian Agricultural Research Corporation, abbreviated to EMBRAPA), Dias (2015) made use of a study elaborated by the strategic management consultancy of the Ministry of Agriculture, Livestock and Food Supply (abbreviated to MAPA, in Portuguese), showing the agricultural income expressed in the Gross Value of Production (GVP) to define the main species/cultures. Subsequently, the author screened a few successful and unsuccessful technologies through royalty payments over the

past few years (2010 – 2015), as well as referring to the date of the cultivar protection – which represents its patent – to identify the leading researchers in the network.

To define innovation performance in the Spanish research network, Dias (2015) elaborated a table with information (cultures, leading researchers, institutions, and contacts) of the most successful Spanish cases in plant breeding in the agricultural research sector. This was accomplished through the collaboration of the Department of International Scientific Affairs and of the Deputy Head of Multilateral Affairs of INIA (*Instituto Nacional de Investigación y Tecnología Agraria y Alimentaria*). For further details on the cases analyzed, data collection procedures, and data analysis, please refer to the original publication by Dias (2015).

Once the causal conditions and innovative performance have been assigned a value (0 – 1), it is possible to carry out the MDSO/MSDO analysis. To exemplify the technique – i.e., the aim of this article – we used the MDSO/MSDO software (version 1.1; available via <https://www.jchr.be/01/v11.htm>).

The first step, measuring similarities and differences, begins with the typing of the dichotomized table in the MDSO/MSDO software; it is important to observe that the typing must start with the successful cases, and one must also observe the separation of the groups (categories). The data collected by Dias (2015) were entered into the software and are represented below (Figure 1).

Outcome
111111111111111111 00000000
Category 1: 4 variables
11111111111110101 111111111
11111111011110101 111111111
11011111011111110 001101111
01111011101000101 110111111
Category 2: 5 variables
11111111111111111 111111111
01101111111001100 000001010
01000101100001000 100000011
11111111111111110 011111111
0001101101000100 000100010
Category 3: 4 variables
10110010100101001 010110110
00001000000000000 001000000
1000000000010000 010000000
01001111011000101 101001111
Category 4: 7 variables
10011010010111101 010111111
11111101101110001 110101101
01010100000010010 011100000
10001111000000000 001011111
00110000001000000 000101000
01010011100000000 111100110
11110100001000001 110101001

Figure 1. Dichotomized table: performance variables and clusters of causal conditions
Note. Figure created using MDSO/MSDO software.

The first partial result provided by the software corresponds to the distance matrices, which consists in aggregating the sums found in each comparison of pairs of each variable. For each cluster (categories 1, 2, 3, and 4), the software calculates a distance matrix. In order to exemplify this partial result, we demonstrate below the distance matrix for Category 1 (Figure 2).

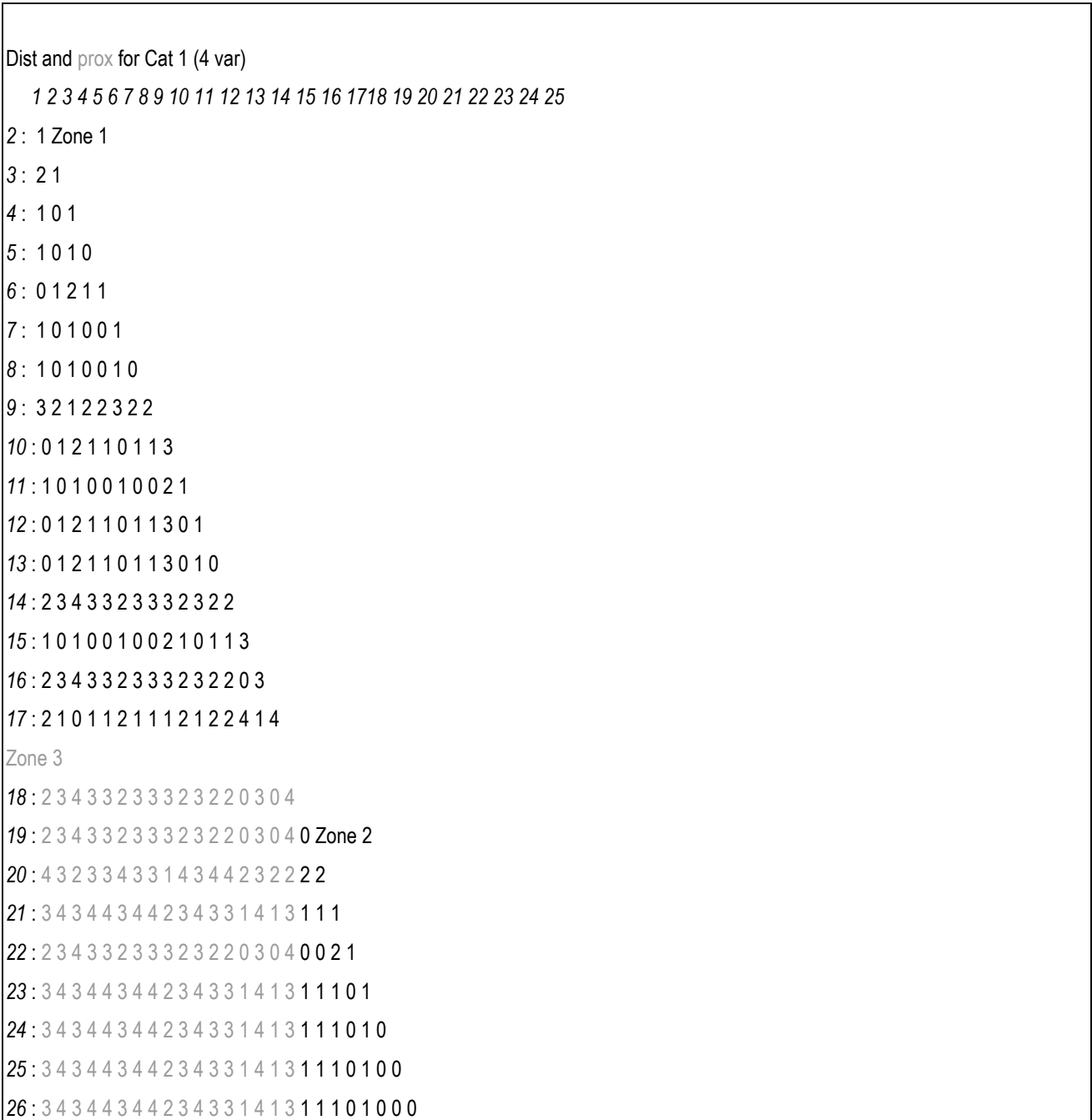


Figure 2. Distance matrix for Category 1(Physical resources)
 Note. Figure created using MDSO/MSDO software.

The information in Figure 2 is shown in three different zones. Zone 1 indicates the comparison between cases with the same outcome (outcome); more precisely, the comparison among cases with Level 1 (success). Zone 2 also represents the comparison among cases with the same outcome (outcome), more precisely, the comparison between cases with Level 0 (failure). Zone 3 indicates the comparison between the cases with Level 1 (success) and the case with Level 0 (failure).

The numbers in the matrix represent the absolute difference between the comparison of cases for each causal condition. For instance, by comparing the pair of cases 1 and 2 for Category 1, the outcome was 1. This means that the sum of the comparison between pairs of the four causal conditions in this category was 1.

The second stage, i.e., determining levels of (dis)similarity, involves the establishment of the levels of similarity and difference. As already mentioned in the previous stage, the distance matrix is composed of different distances between compared pairs. In other words, the aim in this stage is to identify the most different and the most similar pairs.

This analysis is performed for each of the zones in the distance matrix. In Zone 1 (comparison between pairs with the same outcome), for instance, the distance matrix of Category 1 (previous matrix) indicates that the biggest difference between the comparison of pairs is four. In Zone 1 and 2, the most different pairs are particularly important to us because our aim is to identify the most different pairs with similar outcomes (MDSO). Let us take the pair (3, 16) as an example. The intersection is four. The pairs with the biggest difference (four) were identified with Level 0. The pairs with a difference of three were found with Level 1. These are the pairs of interest to be identified, since the other pairs do not represent the biggest differences (differences of two, one, and zero). The same reasoning applies to Zone 2.

In Zone 3 (comparison of pairs with different outcomes), our purpose is to identify the most similar pairs, since the intention of this zone is to identify the most similar pairs with the most different outcomes (MSDO). Let us consider the pairs (4, 21), for instance. The intersection is four. The pairs with the smallest difference (four) were identified with Level 0. The pairs with a difference of three were found with Level 1. These are the pairs of interest to be identified, since the other pairs do not represent the biggest similarities (differences of two, one, and zero).

The definition of the number of levels to be identified is based on the creation of a cut-off score equal to half the number of causal conditions associated with the category (Meur, Bursens & Gottcheiner, 2006). The result of the classification of most different and most similar pairs is presented in the matrix below (Figure 3).



Figure 3. Classification of most different and most similar pairs in Category 1

Note. Figure created using MDSO/MSDO software.

The software offers, as a partial result, a summary of the similarities and differences observed, represented by the levels of the difference (0, 1, 2, 3, and 4) in each cluster (category). It represents a synthesis of the four analysis (4 clusters or categories) conducted in the previous stage (Figure 4).

Subsequently, the software presents a matrix that shows the sum of the level of difference (i) for each comparison pair. For example, in the pair (1, 2) there is no Level 0 (sum 0), there is one Level 1 (zero Level 0 + one Level 1 = sum 1), there is one Level 2 (zero Level 0 + one Level 1 + one Level 2 = sum 2), and no Level 3 or 4; thus, the sum 2 is repeated (zero Level 0 + one Level 1 + one Level 2 + zero Level 3 = sum 2 and zero Level 0 + one Level 1 + one Level 2 + zero Level 3 + zero Level 4 = 2). Hence, the pair (1, 2) indicates the outcome -12222. The outcome 44444, for example, indicates that the four categories are at Level 0. As another example, 24444 means that two categories are at Level 0 and the other two at Level 1 (Figure 5).

Based on the cumulative sum of levels in the matrix, it is possible to determine the highest levels of (dis)similarity in each zone.

In Zone 3 (comparison of pairs with different outcomes), the pair with the greatest similarity (maximum similarity and different outcomes – MSDO) is of our interest. The pairs with greatest similarity would be represented by pairs with four levels “zero” (44444 in the cumulative representation), followed by pairs with three levels “zero” (-4444, 1444, 2444, and 3444), and so on.

In Zone 1 and 2 (comparison of pairs with similar outcome), the pair with the biggest difference (maximum difference and similar outcome – MDSO) is of interest to us. The pairs with the biggest difference would be represented by pairs with four levels “zero” (44444 in the cumulative representation), followed by pairs with three levels “zero” (-4444, 1444, 2444, and 3444), and so on.

Highest levels by Zone

Zone 1: $\Sigma D0=1 \Sigma D1=3 \Sigma D2=3 \Sigma D3=3 \Sigma D4=3 = 13333$

Zone 2: $\Sigma D0=1 \Sigma D1=2 \Sigma D2=2 \Sigma D3=2 \Sigma D4=2 = 12222$

Zone 3: $\Sigma S0=4 \Sigma S1=4 \Sigma S2=4 \Sigma S3=4 \Sigma S4=4 = 44444$



Figura 4. Figure created using Note: MDSO/MSDO software.

Cumulative levels (ΣD_i and ΣS_i , for $i=0$ to 4)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	
	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	01234	
2:	-1222	Zone 1																								
3:	-----																									
4:	--111	-1111	----																							
5:	11111	-1111	-1222	-2222																						
6:	-2222	-----	-----	--111	-----																					
7:	-----	-1111	11111	-1111	-----	-1111																				
8:	-2222	-----	--111	-1111	-----	-----																				
9:	-2333	-----	--111	-1111	-1222	-----	-----																			
10:	-1111	-1111	--111	-1111	-----	-1111	-----	--111	-1111																	
11:	-1111	-----	-----	--111	-----	11111	--111	-----	--111																	
12:	-----	--111	-----	--111	-1111	-1222	-----	-1111	-2222	-----	-----															
13:	-----	--111	-----	-1111	-1111	-1222	-1222	-2222	-----	--111	-----															
14:	-----	-2222	11222	-3333	-2222	-1111	-1111	-1222	-1111	-----	-1222	-----	-----													
15:	-1111	-1111	--111	-1111	-----	-1111	-----	--111	-----	--111	-----	--111	-----	-1111												
16:	-1111	-1111	11222	-2222	-1222	-1111	-1222	-2333	-2222	-----	-1222	-----	-----	-1111												
17:	-----	-1111	-----	-1111	11111	--111	11222	11111	-----	-1111	-----	-1111	12222	-1111	11222											
Zone 3																										
18:	--122	13444	11222	-1122	-2222	11122	-2222	12333	-2222	11111	12333	--122	--111	--111	12222	-1222	13444									
19:	22233	-2333	13333	-4444	-1222	--11	-2222	-1111	-2233	-1111	-1222	12233	12333	-1222	-1222	11111	12333	-1111	Zone 2							
20:	22222	-2344	-1111	-2222	12333	12233	-2333	-2333	---	11	13333	-2333	22222	22222	--111	-2333	11222	-1111	--111	11222						
21:	-3333	11222	12344	44444	12222	-1222	12333	11222	11222	-1222	12233	13333	-2233	11111	12222	-2222	-2344	11111	-----	-2222						
22:	12333	-1222	23333	13333	-2333	-----	-4444	-1122	12222	-2222	-1222	22333	11122	12333	-2333	12233	13344	-1111	-1111	-1111	11111					
23:	-3333	23333	12333	11233	13444	12344	23333	22333	--111	23333	23444	-2233	-2222	-1111	23333	-2222	-2444	11222	-1222	11111	-----	-----				
24:	12333	12333	-3333	13333	12333	-2222	24444	13333	-1222	-3344	12333	13444	12233	-1233	12344	11111	13344	-----	-----	--111	-----	-----				
25:	-1122	13333	-2333	12333	12333	13333	33444	23444	12233	-2444	13333	-2233	-1111	-2333	13444	-----	12222	11222	11222	11111	-1111	11111	--111	11111		
26:	13333	23333	-1233	11222	13333	12444	12344	22344	--111	12344	22233	-2333	-2233	-1122	22233	-2222	-3444	-----	-1111	-1111	--111	-----	-----	-----		

Figure 5. Matrix with the cumulative sum of the difference levels
 Note. MDSO/MSDO software.

$\Sigma S_0 = 4$ means that there are pairs with sum of level 0 = 4, that is, the four pairs (h) with categories with level (D) 0. These pairs represent the highest level of similarity found at Level 0. At that same level, the pairs (h) with level 3, 2, and 1 would also be included in any of the four categories, entering with less similarity. The second highest level of similarity in Zone 3 would be obtained through pairs with $\Sigma S_1 = 4$, that is, pairs with the four categories with level (D)1. In this same level and with less similarity, the pairs (h) with levels 3, 2, and 1 would be included in any of the four categories.

The fourth stage, i.e., identification of causal conditions, begins with the identification of the most different and most similar pairs in each zone provided by the software as a final result (Figure 6).

<p>Outstanding pairs</p> <p>«h» - written down once only</p> <p>Zone 1</p> <p>D0: h=1 (1,5) (3,7) (7,11) (3,14) (3,16) (6,17) (8,17) (9,17) (14,17) (16,17)</p> <p>D1: h=3 (4,14)</p> <p>D2: h=3 (1,9) (8,16)</p> <p>D3: h=3</p> <p>D4: h=3</p> <p>Zone 2</p> <p>D0: h=1 (19,20) (18,21) (21,22) (18,23) (20,23) (18,25) (19,25) (20,25) (22,25) (24,25)</p> <p>D1: h=2 (20,21)</p> <p>D2: h=2 (19,23)</p> <p>D3: h=2</p> <p>D4: h=2</p> <p>Zone 3</p> <p>S0: h=4 (4,21)</p> <p>S1: h=4 (4,19) (7,22) (7,24)</p> <p>S2: h=4 (2,18) (17,18) (5,23) (11,23) (17,23) (12,24) (7,25) (8,25) (10,25) (15,25) (6,26) (17,26)</p> <p>S3: h=4 (2,20) (3,21) (17,21) (17,22) (6,23) (10,24) (15,24) (17,24) (7,26) (8,26) (10,26)</p> <p>S4: h=4</p>
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Figure 6. Most different and most similar pairs in each zone
 Note. Figure created using MDSO/MSDO software.

Through previous results, it is possible to identify the causal conditions that can support the similarities (MDSO) and differences (MSDO) (Figures 7, 8 e 9). In the most different pairs of cases with the same outcome (MDSO), the same conditions are identified. In the most similar pairs with different outcomes (MSDO), pairs of cases with different outcomes are identified (De Meur & Gottcheiner, 2009). The most explanatory causal conditions are those that represent the most the (dis)similarities between the compared pairs. However, in both analyses, we considered only the conditions that are mentioned at least twice in the comparison of (dis)similar pairs (De Meur & Gottcheiner, 2009).

Pairs of compared cases	19	20	18	21	21	22	18	23	20	23	18	25	19	25	20	25	22	25	24	25	Sum of similarities	Order
	BR_Fail_2	BR_Fail_3	BR_Fail_1	BR_Fail_4	BR_Fail_4	BR_Fail_5	BR_Fail_1	BR_Fail_6	BR_Fail_3	BR_Fail_6	BR_Fail_1	BR_Fail_8	BR_Fail_2	BR_Fail_8	BR_Fail_3	BR_Fail_8	BR_Fail_5	BR_Fail_8	BR_Fail_7	BR_Fail_8		
PhyR1_Facilities	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10	1st
PhyR2_Equip	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10	1st
PhyR3_Materials	0	1	0	1	1	0	0	1	1	1	0	1	0	1	1	1	0	1	1	1	3	7th
PhyR4_Service_Infra	1	0	1	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	7	2nd
HumR1_R&D	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10	1st
HumR2_MGTM	0	0	0	0	0	0	0	1	0	1	0	1	0	1	0	1	0	1	0	1	3	7th
HumR3_Com_Align	0	0	1	0	0	0	1	0	0	0	1	1	0	1	0	1	0	1	0	1	4	5th
HumR4_Partnership	1	1	0	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	7	2nd
HumR5_Learning	0	0	0	1	1	0	0	0	0	0	0	1	0	1	0	1	0	1	0	1	1	-
FinR1_Inst_Limit	1	0	0	1	1	1	0	0	0	0	0	1	1	1	0	1	1	1	1	1	6	3rd
FinR2_Inst_Higher	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	7	2nd
FinR3_External	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	7	2nd
FinR4_Inter_Ext	0	1	1	0	0	0	1	1	1	1	1	1	0	1	1	1	0	1	1	1	6	3rd
OrgR1_Intelec_Prop	1	0	0	1	1	1	0	1	0	1	0	1	1	1	0	1	1	1	1	1	4	5th
OrgR2_Org_Str	1	0	1	1	1	0	1	1	0	1	1	0	1	0	0	0	0	0	0	1	3	6th
OrgR3_Processes	1	1	0	1	1	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	3	6th
OrgR4_Image_TM	0	1	0	0	0	1	0	1	1	1	0	1	0	1	1	1	1	1	1	1	4	5th
OrgR5_Org_Cult	0	0	0	1	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	5	4th
OrgR6_Info_Mkt	1	1	1	1	1	0	1	0	1	0	1	1	1	1	1	1	0	1	1	1	6	3rd
OrgR7_Org_Strtg	1	0	1	1	1	0	1	1	0	1	1	0	1	0	0	0	0	0	0	0	4	5th

Figure 7. Comparative analysis of MDSO pairs and identification of explanatory conditions of network failure
 Note: prepared by the author.

Pairs of compared cases	1	5	3	7	7	11	3	14	3	16	6	17	8	17	9	17	14	17	16	17	Sum of similarities	Order
	BR_Succ_1	BR_Succ_5	BR_Succ_3	BR_Succ_7	BR_Succ_7	ES_Succ_2	BR_Succ_3	ES_Succ_5	BR_Succ_3	ES_Succ_7	BR_Succ_6	ES_Succ_8	BR_Succ_8	ES_Succ_8	BR_Succ_9	ES_Succ_8	ES_Succ_5	ES_Succ_8	ES_Succ_7	ES_Succ_8		
PhyR1_Facilities	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	0	1	6	5th
PhyR2_Equip	1	1	1	1	1	1	1	0	1	0	1	1	1	1	0	1	0	1	0	1	6	5th
PhyR3_Materials	1	1	0	1	1	1	0	1	0	1	1	0	1	0	0	0	1	0	1	0	3	8th
PhyR4_Service_Infra	0	1	1	1	1	1	1	0	1	0	0	1	1	1	1	1	0	1	0	1	4	7th
HumR1_R&D	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10	1st
HumR2_MGTM	0	1	1	1	1	1	1	1	1	0	1	0	1	0	1	0	1	0	0	0	4	7th
HumR3_Com_Align	0	0	0	0	0	0	0	1	0	0	1	0	1	0	1	0	1	0	0	0	5	6th
HumR4_Partnership	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	1	0	1	0	5	6th
HumR5_Learning	0	1	0	0	0	1	0	0	0	0	1	0	1	0	1	0	0	0	0	0	4	7th
FinR1_Inst_Limit	1	0	1	1	1	0	1	1	1	0	0	1	0	1	1	1	1	1	0	1	4	7th
FinR2_Inst_Higher	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	2nd
FinR3_External	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	3rd
FinR4_Inter_Ext	0	1	0	1	1	1	0	0	0	0	1	1	1	1	0	1	0	1	0	1	5	6th
OrgR1_Intelec_Prop	1	1	0	1	1	0	0	1	0	0	0	1	0	1	0	1	1	1	0	1	3	8th
OrgR2_Org_Str	1	1	1	0	0	1	1	0	1	0	1	1	1	1	1	1	0	1	0	1	4	7th
OrgR3_Processes	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	7	4th
OrgR4_Image_TM	1	1	0	1	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	7	4th
OrgR5_Org_Cult	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	7	4th
OrgR6_Info_Mkt	0	0	0	1	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	7	4th
OrgR7_Org_Strtg	1	0	1	0	0	1	1	0	1	0	1	1	0	1	0	1	0	1	0	1	1	-

Figure 8. Comparative analysis of MDSO pairs and identification of explanatory conditions of network success

Note: prepared by the author.

Pairs of compared cases	4	21		4	19		7	22		7	24	Sum Differences	Order
	BR_Succ_4	BR_Fail_4		BR_Succ_4	BR_Fail_2		BR_Succ_7	BR_Fail_5		BR_Succ_7	BR_Fail_7		
PhyR1_Facilities	1	1		1	1		1	1		1	1	0	-
PhyR2_Equip	1	1		1	1		1	1		1	1	0	-
PhyR3_Materials	1	1		1	0		1	0		1	1	2	1st
PhyR4_Service_Infra	1	1		1	1		1	1		1	1	0	-
HumR1_R&D	1	1		1	1		1	1		1	1	0	-
HumR2_MGTM	0	0		0	0		1	0		1	0	1	-
HumR3_Com_Align	0	0		0	0		0	0		0	0	0	-
HumR4_Partnership	1	1		1	1		1	1		1	1	0	-
HumR5_Learning	1	1		1	0		0	0		0	0	1	-
FinR1_Inst_Limit	1	1		1	1		1	1		1	1	0	-
FinR2_Inst_Higher	0	0		0	0		0	0		0	0	0	-
FinR3_External	0	0		0	1		0	0		0	0	1	-
FinR4_Inter_Ext	0	0		0	0		1	0		1	1	1	-
OrgR1_Intelec_Prop	1	1		1	1		1	1		1	1	0	-
OrgR2_Org_Str	1	1		1	1		0	0		0	1	1	-
OrgR3_Processes	1	1		1	1		0	0		0	0	0	-
OrgR4_Image_TM	0	0		0	0		1	1		1	1	0	-
OrgR5_Org_Cult	1	1		1	0		0	0		0	0	1	-
OrgR6_Info_Mkt	1	1		1	1		1	0		1	1	1	-
OrgR7_Org_Strtg	1	1		1	1		0	0		0	0	0	-

Figure 9: Comparative analysis of MSDO pairs and identification of explanatory conditions of success vs. failure in networks

Note: prepared by the author.

While an analysis MDSO/MSDO indicates which conditions have the most explanatory potential, it does not provide any guidelines on the number of conditions that should be included in the QCA. Marx and Dusa (2011) provide a benchmark table that lists the maximum number of conditions for which the QCA can distinguish between real and random data for a given number of cases. Presenting 109 cases, this table assigns a maximum of ten conditions. With a high number of conditions, for instance, there would be 1,024 logically possible configurations and, therefore, at least 915 logical remainders. In order to maintain a limited number of possible configurations, Berg-Schlosser and De Meur (2009) suggest including four to seven conditions if there are 10 to 40 cases. Additionally, Berg-Schlosser and De Meur (2009) and Schneider and Wagemann (2012) argue that the ideal balance between the number of conditions and cases is not purely numerical, but should result from an interactive dialogue between the previous theoretical knowledge and empirical ideas that arise during the research process. However, if the sample is too small, the MSDO method may lead to a reduction of conditions, allowing the identification of causal conditions that may be responsible for the different outcomes between samples (Berg-Schlosser, & De Meur, 2009).

Considering that in our example 26 networks are being analyzed, seven causal conditions are proposed for the explanatory QCA of failure (Figure 10), another seven causal conditions for the explanatory QCA of success (Figure 11), and explanatory conditions for the difference between success and failure (Figure 12), which should be included in both QCA (success and failure).

Order	Causal conditions
1st	PhyR1_Facilities
1st	PhyR2_Equip
1st	HumR1_R&D
2nd	PhyR4_Service_Infra
2nd	HumR4_Partnership
2nd	FinR2_Inst_Higher
2nd	FinR3_External

Figure 10. Selected causal conditions for the analysis of network failure

Note: prepared by the author.

Order	Causal conditions
1st	HumR1_R&D
2nd	FinR2_Inst_Higher
3rd	FinR3_External
4th	OrgR3_Processes
4th	OrgR4_Image_TM
4th	OrgR5_Org_Cult
4th	OrgR6_Info_Mkt

Figure 11. Selected causal conditions for the analysis of network success

Note: prepared by the author.

Order	Causal condition
1st	PhyR3_Materials

Figure 12. Selected causal conditions for the analysis of performance difference

Note: prepared by the author.

The identification of the conditions that explain the differences in the innovative performance of the networks through the MDSO/MSDO technique reduced the number of explanatory causal conditions from 20 to seven causal conditions that explain the success in innovation; seven causal conditions that explain the failure in innovation; and one more condition that explains the difference between success and failure in innovation, thus enabling the analysis of sufficiency provided by the QCA method and the assessment of how these conditions can be combined; i.e., the fundamental contribution of the csQCA method. Based on the findings provided herein for the identification of the explanatory configurations of successful innovation in networks, it is necessary to use the seven explanatory conditions for success (Figure 5), plus one explanatory condition for the difference in performance (Figure 6).

4. FINAL CONSIDERATIONS

The aim of this article was to analyze and exemplify each of the four stages of the MDSO/MSDO method. To this end, the technique was applied to identify the causal conditions that explain the difference in performance of 26 agricultural innovation networks in Brazil and Spain.

The 20 causal conditions were grouped into four categories (clusters), namely Physical Resources, Human Resources, Financial Resources, and Organizational Resources. With the application of the MDSO/MSDO technique of comparative analysis, seven causal explanatory conditions were identified for successful innovation; seven causal explanatory conditions for failing innovation; plus one causal explanatory condition for the difference between successful and failing innovation. The reduction of the number of causal conditions contributes to reducing the complexity of the system while maintaining the relevant information of the phenomenon under analysis.

Reducing complexity allows the reassessment of the analyzed cases to pursue a more in-depth analysis of the differences found. It also promotes the accomplishment of further studies based on the csQCA technique, which is an appropriate procedure for the comparative analysis of a medium or small number of cases, and requires fewer causal conditions for analysis.

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