Socio-economic and health management of pandemics based on Forgotten Effects Theory

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Abstract

Societies experience intense and frequent changes in various environments, which increases uncertainty and complexity in decision-making. The pandemic caused by COVID-19 exacerbates this situation. Companies and individuals had to adapt to new rules and change their work and consumer behavior. Therefore, the decision-maker seeks to reduce risks and meet these new challenges. In this context, science plays a vital role in managing the crisis. The aims of the article are: to promote awareness of the increase in uncertainty and how this can generate negative impacts that affect decision making; to indicate how the fuzzy logic can help in the reduction of risks by facilitating decision making; and to know the forgotten effects of the pandemic on society. This study is applied research, with a quantitative modelling and simulation approach through the Forgotten Effects Theory. The main contribution is to show the usefulness of an algorithm that allows identifying forgotten effects and preventing future crises. The results allow us to predict and act more effectively on the causes, thus minimizing the effects of the crisis in society. There is an enormous potential for future lines of research on the subject.

Keywords: decision-making, uncertainty, forgotten effects, fuzzy logic, COVID-19.

Introduction

Societies experience intense and frequent changes in various environments, which increases uncertainty and complexity in decision making. Recent changes in some countries in the social, political, economic, health, and environmental fields reinforce this statement and are the primary motivation for the study. It should be noted that the cases presented are not intended to exhaust the discussion on the subject, and indeed the aim is to promote awareness of the increase in uncertainty and how this can generate negative impacts affecting decision-making.

Firstly, it can be seen that socio-political uncertainty has increased in several parts of the world. At this point, we can see the combination of social and political factors that increase uncertainty. In general, misguided policies, citizens' desire for a better world, and justice can be seen as the leading causes of increased socio-political uncertainty. In 2019 there were demonstrations and disturbances in Latin American countries [1], for example, in Chile with social dissatisfaction with the rise in public transport prices and fights for better living conditions. On the other hand, in

Peru, there were widespread protests against corruption and social conflicts. In Brazil, the demonstrations reflected the Amazon's defense, the fight against corruption, the cuts in education budgets, and the high unemployment rate. In Bolivia, widespread dissatisfaction led to the impeachment of President Evo Morales. Other issues generated increased socio-political uncertainty in the region, for example, in Colombia, with the announcement of the return of the Revolutionary Armed Forces of Colombia and a possible threat to peace. In Argentina and Mexico, the increase in uncertainty was related to the return of leftist parties to power, the economic crisis, and increased violence rates. In Venezuela, with the economic collapse, the permanence of Nicolas Maduro as president generates social tensions and possible international interference to solve this crisis. In 2020, another study demonstrates this fragility and argues that "the COVID-19 pandemic is testing all Latin American countries' socio-economic fabric and political leadership" [2].

Another report [3] indicates that in 2019 the "United States continued to lead a retreat in human rights". The result was more strict immigration policies, continued racism and discrimination, undermining women's rights and the lesbian, gay, bisexual, and transgender (LGBT) community. Further weakened Americans' ability to access adequate health care and deregulated industries that put people's health and safety at risk.

In Europe, too, we saw the rise of socio-political uncertainty, for example, in France with the yellow vest protests, the welfare reform, and the terrorist attacks[4]; in Spain with the separatist movement in Catalonia and the lack of consensus informing the government [5]. The political crisis was also seen in Italy [6]; and the United Kingdom with the Brexit process [7]. All these socio-political issues that seem to be isolated end up harming the countries' economies and families' well-being and evidence a rise in risks for an entire region. The lack of leadership at the global level also causes political uncertainty [8]. Fig 1 shows the five main fields of uncertainty presented in this manuscript.

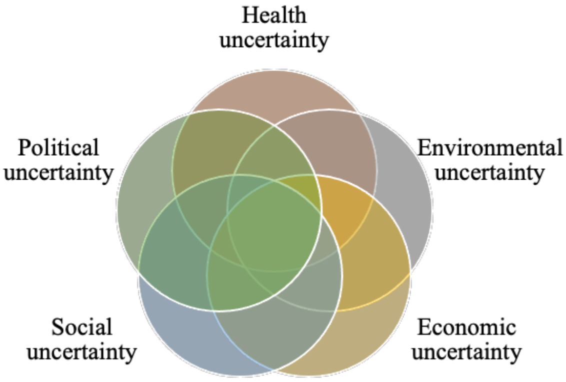


Fig. 1. Fields of uncertainty. Source: own elaboration.

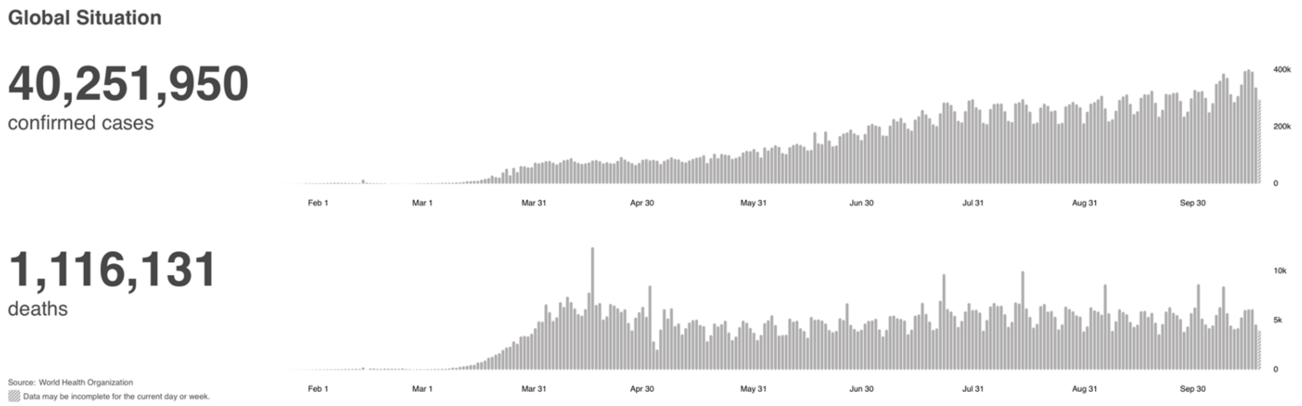
Second, social uncertainty increased significantly in 2019 due to migration in various parts of the world and the expansion in the number of refugees. Also, social tension is rising with the crisis in Syria and armed conflicts in the Middle East [3]. The consequences are the struggle for the guarantee of human rights, lack of reception infrastructure, increasing inequalities, and intolerance towards foreigners. In short, social issues can trigger political instability, economic crisis, increasing inequalities and poverty, unemployment and violence.

Third, to put the economic uncertainty into context, 2019 saw a US trade war with China [9], and trade restrictions through the raising of US import tariffs on products from various countries. Already in March 2020, the COVID 19 pandemic caused a drop in global demand for crude oil, which contributed to lower oil prices and increased tensions between Saudi Arabia, Russia and the United States [10]. The result is negative investment expectations, low gross domestic product (GDP) growth, unemployment and increased social inequalities.

Fourth, environmental uncertainty has increased in recent years due to global warming and climate change. Studies [11], [12] indicate that the increase in temperature between 1.5ºC and 2.0ºC can reduce the availability of freshwater for human consumption by 9% to 17% respectively. An increase in heavy rainfall and flooding, a reduction in agricultural crop yields, and a rise in sea levels are also predicted. These results expected to increase migration due to climate change, accentuating social and economic tensions. Besides, a social crisis with low food production is expected. In this context, in recent years there has been an increase in protests around the world demanding more effective actions from politicians to reduce global warming [13].

Finally, the uncertainty in health highlighted from December 2019, due to the discovery of the new coronavirus causing COVID-19 in Wuhan, China. On March 13, 2020, the director of the World Health

Organization (WHO), Tedros Adhanom Ghebreyesus, declares the coronavirus Covid-19 a global pandemic



after emphasizing that on this date there were more than 118,000 cases of coronavirus in 114 countries. In seven months after the declaration of the pandemic, the situation worldwide worsened considerably according to reported to WHO "Globally, as of 11:47 am CEST, October 20 2020, there have been 40,251,950 confirmed cases of COVID-19, including 1,116,131 deaths" (Fig 2) [14].

Fig. 2. COVID-19 evolution in 2020. Source: World Health Organization [14].

Of the total number of confirmed cases in various regions of the world: 18,800,094 in the Americas, 8,546,666 in South-East Asia, 8,161,571 in Europe, 2,786,477 in the Eastern Mediterranean, 1,267,664 in Africa and 688,737 in the Western Pacific [14]. Fig 3 shows in detail the evolution of the COVID-19 by region in 2020. The results indicate the emergence of a second wave of pollutants in Europe and the Eastern Mediterranean and the maintenance of high levels of cases in the Americas and South-East Asia.

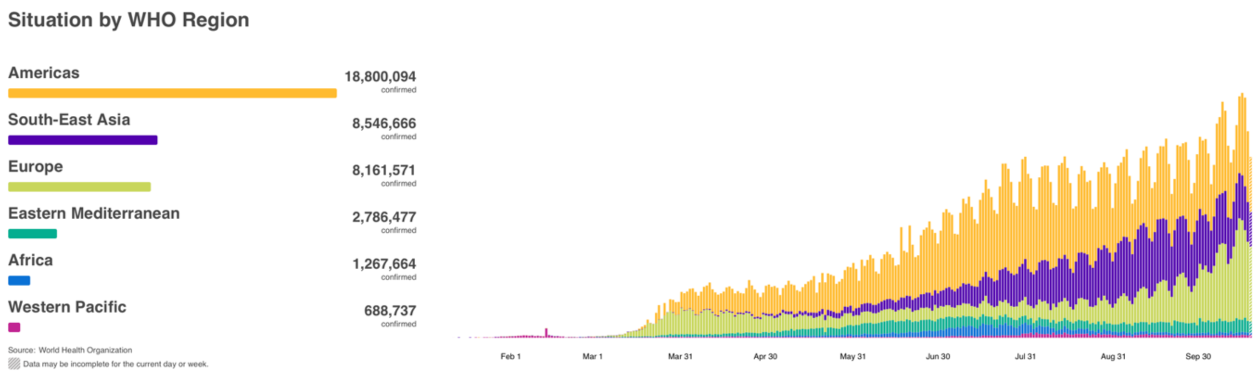


Fig. 3. Evolution of COVID-19 by region in 2020. Source: World Health Organization [14].

This health crisis already shows a negative impact on the lives of millions of people around the world. It may collapse the entire global economic system, generating increased social and political tensions in nations [1]. Uncertainty in health is affecting, globally and at the same time, the social, political, economic and environmental fields.

In summary, the pandemic caused by COVID-19 simultaneously changed several elements in the five areas cited above, including social isolation, remote working growth, intensified citizen control, expansion of business virtualization, pollution reduction, reduction in agricultural productivity, rise in unemployment, reduction in Gross Domestic Product (GDP), increasing poverty, restriction of mobility, mental distress, lack of political leadership, an extension of public debt, closure of companies, shifting consumption patterns, health services shortage, and increased hygiene requirements [8], [15]–[20]. Therefore, there is interdependence between each of the areas, thus generating greater complexity in the decision. With this, the decision-maker is looking for tools that reduce risks and facilitate decision making in order to face these new challenges.

In this context, science plays an essential role in proposing new solutions. Appropriately, it is gathered in Fuzzy Logic [21] to orient the application of decision models in the problems with which society currently passes. The mathematics of uncertainty showed useful in various areas of knowledge, such as engineering, biology, medicine, management, finance, human resources, geology, sociology, among others [22]. For this reason, it is defined as an object of study in this article. As indicated in other studies [23], [24], decisions in the real world take place in uncertain environments where the consequences of actions are not precisely known. An application of fuzzy logic precisely considers the intersection of objectives and constraints within a multi-stage process in which human subjectivity influences the decision.

The research undertaken can be classified as applied, with the explanatory objective and quantitative approach, through modeling and simulation [25]. The most critical limitation refers to the number of causes and effects that were included in the analysis. The main contribution is to show the usefulness of an algorithm that allows to identify forgotten effects and prevent future crises. The results allow us to predict and act more effectively on the causes, thus minimizing the effects of the crisis on society.

The aims of the article are: to promote awareness of the increase in uncertainty and how this can generate negative impacts that affect decision making; to indicate how the fuzzy logic can help in the reduction of risks by facilitating decision making; and to know the forgotten effects of the pandemic on society. The article is structured as follows: Section 2 presents the methodology used. Section 3 shows the results and discussion. Section 4 describes the conclusion, contributions and future lines of research.

Materials and Methods

This section presents the methodology used to carry out, in the specific case, we chose the Forgotten Effects Theory [26]. This algorithm proved to be a handy tool in the field of social science, economics or management because it allows the assessment of the relationship between causes and effects [27]–[29]. From the results, it is possible to identify the existence of an interposed element enhancing and accumulating effects in the causal relationship. Therefore, the results make it possible to predict and act more effectively on the causes, thus minimizing the effects.

The approach starts with the existence of a direct incidence relationship; that is, an uncertain cause-effect matrix defined by two sets of elements: $A = \{a_i / i = 1,2, \dots, n\}$ which act as causes; $B = \{b_j / j = 1,2, \dots, m\}$ which act as effects and a causality relationship $\tilde{M}$ defined by the $n \times m$ dimension matrix:

$$[\tilde{M}] = \left\{\mu_{a_i b_j} \in [0,1] / i = 1,2, \dots, n; j = 1,2, \dots, m\right\}$$

being $\mu(a_i, b_j)$ of the values the characteristic function of belonging of each one of the elements of the matrix $\tilde{M}$ (formed by the rows corresponding to the elements of the set - causes - and the columns corresponding to the elements of the set - effects).

It can be said, then, that the matrix $\tilde{M}$ is composed of the estimates made around all the effects that the elements of set A exert on the elements of set B. The more significant this incidence ratio is, the higher the valuation assigned to each of the elements of the matrix. In this case, since it is assumed that the characteristic function of belonging had to belong to the interval$[0,1]$, it is understood that the higher the incidence ratio, the closer to 1 the assigned valuation is. Conversely, the weaker a causal relationship between two elements is considered, the closer the corresponding valuation is to 0. It should be emphasized that this initial matrix $\tilde{M}$ is elaborated from direct cause-effect relationships; that is, from the first generation.

The objective of this study is based on obtaining a new matrix of incidences that not only reflects the direct causal relationships, but also those that, although not evident, exist and are sometimes fundamental for the appreciation of a phenomena. In order to achieve this objective, it is necessary to establish the devices that determine that different causes may have effects on themselves and, at the same time, take into account that certain effects may also give rise to incidences on themselves. For this reason, it is necessary to build two additional incident relationships, which include the possible effects derived from relating both causes to each other and effects on each other. These two auxiliary matrices are square matrices that are expressed as follows:

$$[\tilde{A}] = \left\{\mu_{a_i a_j} \in [0,1]/i\,, j = 1,2, \dots, n\right\}$$

$$[\tilde{B}] = \left\{\mu_{b_i b_j} \in [0,1]/i\,, j = 1,2, \dots, m\right\}$$

Matrix $[\tilde{A}]$ lists the incidence relations that can occur between each of the elements that act as causes and matrix $[\tilde{B}]$ lists the incidence relations that can occur between each of the elements that act as effects. Both $[\tilde{A}]$ and $[\tilde{B}]$ coincide in the fact that both are reflective matrices, that is to say:

$$\mu_{a_i a_j} = 1\ \forall_{i=1,2,\dots,n}$$

$$\mu_{b_i b_j} = 1\ \forall_{j=1,2,\dots,m}$$

This means that an element, whether cause or effect, affects itself with the greatest presumption. Neither $[\tilde{A}]$ nor $[\tilde{B}]$ are symmetrical matrices, there is at least some pair of subscripts i, j so: $\mu_{a_i a_j} \neq \mu_{a_j a_i}$ *and* $\mu_{b_i b_j} \neq \mu_{b_j b_i}$.

Once the matrices $[\tilde{M}]$, $[\tilde{A}]$ and $[\tilde{B}]$ have been constructed, direct and indirect incidences are established; that is, incidences in which, at the same time, some cause or effect intervenes. For this the max-min composition of the three matrices is used: $[\tilde{A}] \circ [\tilde{M}] \circ [\tilde{B}] = [\tilde{M}^*]$.

The order in the composition must always allow the number of elements in the row of the first matrix to coincide with the number of elements in the column of the second matrix. The result obtained is a new $[\tilde{M}^*]$ matrix that collects the incidences between second generation causes and effects, or the initial causal relationships affected by the possible interposed incidence of some cause or effect. In this sense the matrix is:

$$[\tilde{M}^*] \quad = \quad \begin{array}{cccccc} \Rsh & b_1 & b_2 & \cdots & b_m \\ a_1 & {\mu^*}_{a_1 b_1} & {\mu^*}_{a_1 b_2} & \cdots & {\mu^*}_{a_1 b_m} \\ a_2 & {\mu^*}_{a_2 b_1} & {\mu^*}_{a_2 b_2} & \cdots & {\mu^*}_{a_2 b_m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_n & {\mu^*}_{a_n b_1} & {\mu^*}_{a_n b_2} & \cdots & {\mu^*}_{a_n b_m} \end{array}$$

From this new matrix $[\tilde{M}^*]$, the difference between the second-generation effects matrix and the direct incidences matrix will allows for the determination of the degree to which some causality relationships have been forgotten or ignored: $[\tilde{F}] = [\tilde{M}^*] - [\tilde{M}]$

$$[\tilde{F}] = \begin{array}{cccc} \Rsh & b_1 & \cdots & b_m \\ a_1 & {\mu^*}_{a_1 b_1} - \mu_{a_1 b_1} & \cdots & {\mu^*}_{a_1 b_m} - \mu_{a_1 b_m} \\ a_2 & {\mu^*}_{a_2 b_1} - \mu_{a_1 b_1} & \cdots & {\mu^*}_{a_2 b_m} - \mu_{a_2 b_m} \\ \vdots & \vdots & \vdots & \vdots \\ a_n & {\mu^*}_{a_n b_1} - \mu_{a_n b_1} & \cdots & {\mu^*}_{a_n b_m} - \mu_{a_n b_m} \end{array}$$

Using the degree of forgetfulness of some incident, it is possible to determine the element (cause or effect) that acts as a link. To do this, the steps made from the max-min composition of the matrices indicated in Fig 4 must be followed.

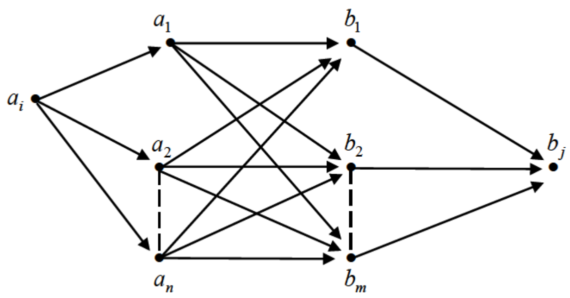


Fig. 4. The max-min composition of the matrices.

Finally, the higher the corresponding value between an element a_i and an element b_j of the characteristic function of belonging to the matrix $[\tilde{F}]$, the higher the degree of oblivion between a_i and b_j produced in the initial relationship and incidence. This means that the implications derived from incidents that are not considered or taken into account in their proper intensity may give rise to erroneous or, at the very least, badly valued actions. In the next section the results of the study are presented.

Results and discussion

Firstly, it is necessary to define a set of causes and effects. In this research, the causes were defined based on scientific studies [1], [4]–[7], [9], [10], [13] and behaviors observed in a western economy. On the other hand, the effects correspond to the changes caused by the COVID-19 pandemic presented in this manuscript [8], [15]–[20]. The processing data used Fuzzylog© software. Secondly, based on the group of three experts' validations, the set of C elements were considered. Table 1 presents the causes and effects.

Table 1. Causes and effects

	Causes	**Effects**
1	Health care	Social isolation
2	Social stability	Remote working growth
3	Political stability	Intensified citizen control
4	Climate of the country	Expansion of business virtualization
5	Natural resources	Pollution reduction
6	Economic stability	Reduction in agricultural productivity
7	Social Justice	Rise in unemployment
8	Family welfare	Reduction in GDP
9	Level of corruption	Increasing poverty
10	Level of education	Restriction of mobility
11	Terrorist attacks	Mental distress
12	Price of energy	Lack of political leadership
13	Access to technology	Extension of public debt
14	Investment in R+D+i	Closure of companies
15	Migration	Shifting Consumption Patterns
16	Armed conflicts	Health services shortage
17	Trade Wars	Increased hygiene requirements

Thirdly, the experts assessed the causes and effects. Semantic correspondence was used for 11 values, from 0 to 1 (the so-called endecadarian scale), with the level of truth in the notion of incidence. The value 0 means no incidence, and the value 1 means the most significant incidence. In the "Direct Incident Matrix" $[\tilde{M}]$, the cause-effect relationships showed in different degrees that are produced between the elements of set C (causes) and the elements of set E (effects), as presented in Fig 5. However, this initial matrix $[\tilde{M}]$ is elaborated from experts' opinions and represents direct cause-effect relationships: first-generation. The objective is to obtain a new matrix of incidences that reflects the direct causal relationships and those that, although they not evident, exist and are sometimes fundamental for the appreciation of the phenomena.

↱	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}	E_{11}	E_{12}	E_{13}	E_{14}	E_{15}	E_{16}	E_{17}
C_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
C_2	0	0,7	0	0,8	0	0	0	0	0	0	0	0	0	0	0	0	0
C_3	0	0,8	0	0,7	0	0	0	0	0	0	0	0	0	0	0	0	0
C_4	0	0	0	0	0	0,8	0	0	0	0	0	0	0	0	0	0	0
C_5	0	0	0	0	0,7	0,3	0	0	0	0	0	0	0	0	0	0	0
C_6	0	0,8	0	0,7	0	0	0	0	0	0	0	0	0	0	0	0	0
C_7	0	0	0	0	0	0	0	0	0	0	0	0	0,6	0	0	0	0
C_8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,7	0	0
C_9	0	0	0	0	0	0	0,9	0,8	0,7	0	0	0,4	0,8	0,5	0	0,8	0
C_{10}	0	0,8	0	0,7	0	0	0	0	0	0	0	0	0	0	0	0	0
C_{11}	0	0	0	0	0	0	0,6	0,5	0,5	0,6	0,4	0	0	0,2	0	0	0
C_{12}	0	0,4	0	0,4	0	0	0	0,3	0,2	0	0	0	0,2	0	0	0	0
C_{13}	0	0,8	0,8	0,8	0	0	0	0	0	0	0	0	0	0	0,5	0	0
C_{14}	0	0,8	0	0,8	0	0	0	0	0	0	0	0	0	0	0	0	0
C_{15}	0	0	0,5	0	0	0	0,6	0,5	0,5	0	0	0	0,3	0	0	0,4	0
C_{16}	0	0	0	0	0	0	0,4	0,5	0,4	0,3	0,4	0	0,3	0	0	0,6	0
C_{17}	0	0	0	0	0	0	0,8	0,7	0,4	0	0	0	0	0,2	0,2	0	0

Fig. 5. Direct Incident Matrix.

It is necessary to establish the devices that make it possible for different causes to have effects on themselves and, at the same time, take into account that specific effects may also affect themselves. For this reason, it is necessary to construct two relations of further incidences that include the possible effects derived from relating causes to each other, on the one hand, and effects to each other, on the other. The experts' opinions are again requested to assess the existing incidences between the causes, establishing a square matrix $[\tilde{A}]$ and the matrix $[\tilde{B}]$ with the existing incidences among the effects. Once the matrices $[\tilde{M}]$, $[\tilde{A}]$ and $[\tilde{B}]$ constructed, direct and indirect incidences established, that is to say, incidences in which, at the same time, some cause or effect intervenes. For this purpose, the max-min composition of the three matrices is carried out: $[\tilde{A}] \circ [\tilde{M}] \circ [\tilde{B}] = [\tilde{M}^*]$. Fig 6 shows the composition max-min between $[\tilde{A}]$ and $[\tilde{M}]$.

↱	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}	E_{11}	E_{12}	E_{13}	E_{14}	E_{15}	E_{16}	E_{17}
C_1	0	0,8	0	0,8	0	0	0	0	0	0	0	0	0,6	0	0,7	1	1
C_2	0	0,8	0	0,8	0	0	0	0	0	0	0	0	0,6	0	0,6	0,4	0,4
C_3	0	0,8	0	0,8	0	0	0	0	0	0	0	0	0,6	0	0,7	0,9	0,9
C_4	0	0,2	0	0,2	0,7	0,8	0	0	0	0	0	0	0	0	0	0	0
C_5	0	0,3	0	0,3	0,7	0,4	0	0	0	0	0	0	0	0	0,4	0	0
C_6	0	0,8	0	0,8	0	0	0	0	0	0	0	0	0	0	0	0,9	0,9
C_7	0	0,7	0,5	0,8	0	0	0,5	0,5	0,5	0	0	0	0,6	0	0,6	0,4	0
C_8	0	0,6	0	0,6	0	0	0	0	0	0	0	0	0,6	0	0,7	0,4	0,4
C_9	0	0,8	0	0,7	0	0	0,9	0,8	0,7	0	0	0,4	0,8	0,5	0,5	0,8	0
C_{10}	0	0,8	0,8	0,8	0	0	0	0	0	0	0	0	0,5	0	0,5	0	0
C_{11}	0	0,7	0	0,7	0	0	0,6	0,5	0,5	0,6	0,4	0	0	0,2	0	0,6	0,6
C_{12}	0	0,5	0	0,5	0	0	0	0,3	0,2	0	0	0	0,2	0	0	0	0
C_{13}	0	0,8	0,8	0,8	0	0	0	0	0	0	0	0	0	0	0,5	0	0
C_{14}	0	0,8	0,8	0,8	0	0	0	0	0	0	0	0	0	0	0,5	0	0
C_{15}	0	0	0,5	0	0	0	0,6	0,5	0,5	0	0	0	0,4	0	0,3	0,4	0
C_{16}	0	0,7	0	0,7	0	0	0,6	0,5	0,5	0,6	0,4	0	0,6	0,2	0,5	0,6	0
C_{17}	0	0,6	0	0,6	0	0	0,8	0,7	0,4	0	0	0	0	0,2	0,2	0	0

Fig. 6. Composition max-min between $[\tilde{A}]$ and $[\tilde{M}]$.

The result obtained is a new matrix $[\tilde{M}^*]$, cumulative effects matrix (Figure 7), which collects the incidences between second-generation causes and effects, or the initial causal relationships affected by the possible interposed incidence of some cause or effect.

Finally, the difference between the cumulative effects matrix and the direct incidences matrix allows for determining of the degree to which some causality relationships have been forgotten.

The forgotten effects matrix is then obtained $[\tilde{F}] = [\tilde{M}^*] - [\tilde{M}]$. Fig 7 shows the Forgotten Effects Matrix.

	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}	E_{11}	E_{12}	E_{13}	E_{14}	E_{15}	E_{16}	E_{17}
C_1	0,8	0,8	0,7	0,8	0,8	0	0,9	0,8	0	0	0,9	0,8	0,8	0	0,8	1	1
C_2	0,8	0,8	0,7	0,8	0,8	0	0,6	0,6	0	0	0,4	0,4	0,6	0	0,8	0,6	0,6
C_3	0,8	0,8	0,7	0,8	0,8	0	0,9	0,8	0	0	0,9	0,8	0,8	0	0,8	0,9	0,9
C_4	0,2	0,2	0,2	0,2	0,7	0,8	0,8	0,7	0,7	0	0	0	0	0,2	0,2	0	0,2
C_5	0,4	0,4	0,3	0,4	0,7	0,4	0,4	0,4	0,4	0	0	0	0	0,2	0,4	0	0,4
C_6	0,8	0,8	0,7	0,8	0,8	0	0,9	0,8	0	0	0,9	0,8	0,8	0	0,8	0,9	0,9
C_7	0,7	0,8	0,7	0,8	0,7	0	0,6	0,6	0,5	0,5	0,5	0,4	0,6	0,5	0,8	0,6	0,6
C_8	0,7	0,7	0,6	0,7	0,7	0	0,7	0,7	0	0	0,4	0,4	0,6	0	0,7	0,6	0,7
C_9	0,8	0,8	0,7	0,8	0,8	0,4	0,9	0,8	0,8	0	0,8	0,8	0,8	0,9	0,7	0,8	0,8
C_{10}	0,8	0,8	0,8	0,8	0,8	0	0,6	0,5	0	0,7	0,8	0	0,5	0	0,8	0,5	0,7
C_{11}	0,7	0,7	0,7	0,7	0,7	0	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,7	0,6	0,6
C_{12}	0,5	0,5	0,5	0,5	0,5	0	0,3	0,3	0,3	0	0,3	0	0,2	0,3	0,5	0,3	0,5
C_{13}	0,8	0,8	0,8	0,8	0,8	0	0,6	0,5	0	0,7	0,8	0	0	0	0,8	0	0,7
C_{14}	0,8	0,8	0,8	0,8	0,8	0	0,6	0,5	0	0,7	0,8	0	0	0	0,8	0	0,7
C_{15}	0,5	0,5	0,5	0,4	0,4	0	0,6	0,6	0,6	0,5	0,6	0,4	0,6	0,6	0,5	0,5	0,5
C_{16}	0,7	0,7	0,7	0,7	0,7	0	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,7	0,6	0,6
C_{17}	0,6	0,6	0,6	0,6	0,6	0	0,8	0,8	0,7	0	0,6	0	0,7	0,8	0,6	0,7	0,6

Fig. 7. Cumulative effects matrix$\left[\widetilde{M}^{*}\right]$.

The results presented in Fig 8 demonstrate that the cause-to-effect relationships that were initially rated 0 (i.e., no incidence) in the direct incidence matrix showed a strong incidence relationship of 0.9 by the end of the forgotten effects matrix, with which it had been forgotten to consider a critical incidence.

	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}	E_{11}	E_{12}	E_{13}	E_{14}	E_{15}	E_{16}	E_{17}
C_1	0,8	0,8	0,7	0,8	0,8	0	0,9	0,8	0	0	0,9	0,8	0,8	0	0,8	0	0
C_2	0,8	0,1	0,7	0	0,8	0	0,6	0,6	0	0	0,4	0,4	0,6	0	0,8	0,6	0,6
C_3	0,8	0	0,7	0,1	0,8	0	0,9	0,8	0	0	0,9	0,8	0,8	0	0,8	0,9	0,9
C_4	0,2	0,2	0,2	0,2	0,7	0	0,8	0,7	0,7	0	0	0	0	0,2	0,2	0	0,2
C_5	0,4	0,4	0,3	0,4	0	0,1	0,4	0,4	0,4	0	0	0	0	0,2	0,4	0	0,4
C_6	0,8	0	0,7	0,1	0,8	0	0,9	0,8	0	0	0,9	0,8	0,8	0	0,8	0,9	0,9
C_7	0,7	0,8	0,7	0,8	0,7	0	0,6	0,6	0,5	0,5	0,5	0,4	0	0,5	0,8	0,6	0,6
C_8	0,7	0,7	0,6	0,7	0,7	0	0,7	0,7	0	0	0,4	0,4	0,6	0	0	0,6	0,7
C_9	0,8	0,8	0,7	0,8	0,8	0,4	0	0	0,1	0	0,8	0,4	0	0,4	0,7	0	0,8
C_{10}	0,8	0	0,8	0,1	0,8	0	0,6	0,5	0	0,7	0,8	0	0,5	0	0,8	0,5	0,7
C_{11}	0,7	0,7	0,7	0,7	0,7	0	0	0,1	0,1	0	0,2	0,6	0,6	0,4	0,7	0,6	0,6
C_{12}	0,5	0,1	0,5	0,1	0,5	0	0,3	0	0,1	0	0,3	0	0	0,3	0,5	0,3	0,5
C_{13}	0,8	0	0	0	0,8	0	0,6	0,5	0	0,7	0,8	0	0	0	0,3	0	0,7
C_{14}	0,8	0	0,8	0	0,8	0	0,6	0,5	0	0,7	0,8	0	0	0	0,8	0	0,7
C_{15}	0,5	0,5	0	0,4	0,4	0	0	0,1	0,1	0,5	0,6	0,4	0,3	0,6	0,5	0,1	0,5
C_{16}	0,7	0,7	0,7	0,7	0,7	0	0,2	0,1	0,2	0,3	0,2	0,6	0,3	0,6	0,7	0	0,6
C_{17}	0,6	0,6	0,6	0,6	0,6	0	0	0,1	0,3	0	0,6	0	0,7	0,6	0,4	0,7	0,6

Fig. 8. Forgotten Effects Matrix $\left[\widetilde{F}\right]$.

Table 4 shows the cause-effect relationships that presented extreme incidences of 0.9 and recovered with the model's application.

Table 4. Cause-effect relationships

Causes	Effects
(C_1) Heath care	(E_{11}) Mental distress
(C_2) Social stability	(E_{15}) Shifting consumption patterns
(C_3) Political stability	(E_{17}) Increased hygiene requirements
(C_6) Economic stability	(E_{16}) Health services shortage
(C_7) Social justice	(E_{15}) Shifting consumption patterns
(C_9) Level of corruption	(E_{11}) Mental distress

Next, an analysis of the cause-effect relationships identified in the forgotten effects' matrix presented, thus observing the elements that most contributed to the indirect effects. Firstly, Fig 9 presents the variation in incidence between health care and mental distress (incidence C_1, E_{11}).

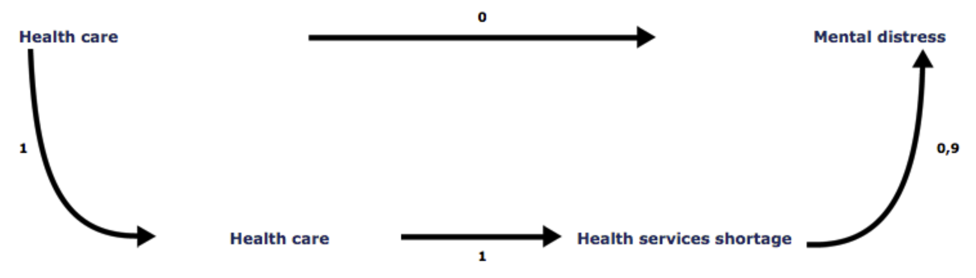


Fig. 9. Incidence variation (forgotten effect) between the Health care cause and the Mental distress effect.

This incidence ratio indicates that although an initial estimate of 0 was established in the Health care incidence on Mental distress, in reality, this ratio increases to 0.9 given that there is an interposed element (Health services shortage) that potentiates and accumulates effects in the causality relationship. Fig 10 shows the full graph of incidences of health care's cause on the effect of Mental distress.

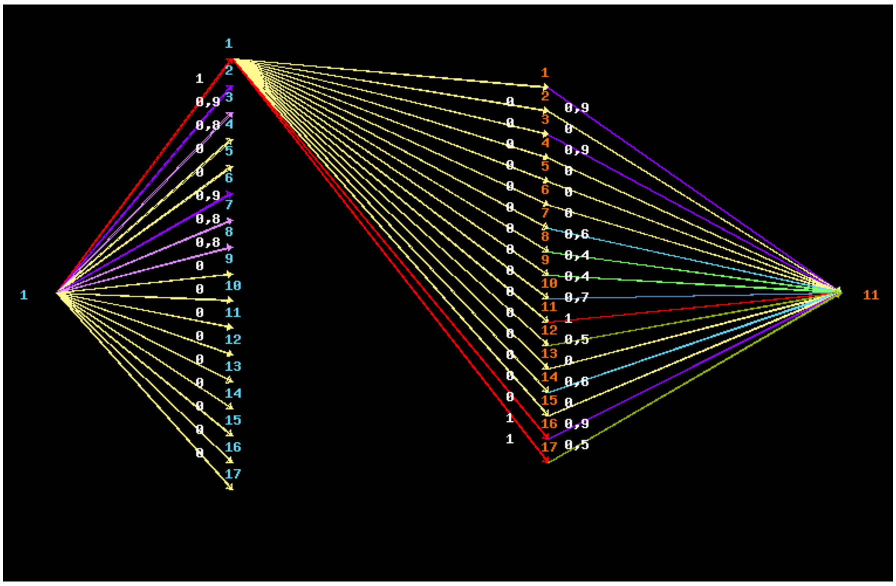


Fig. 10. Full graph of incidences of the cause Health care on the effect Mental distress.

Secondly, Fig 11 displays the incidence variation between Social stability and Shifting consumption patterns (incidence C_2, E_{15}).

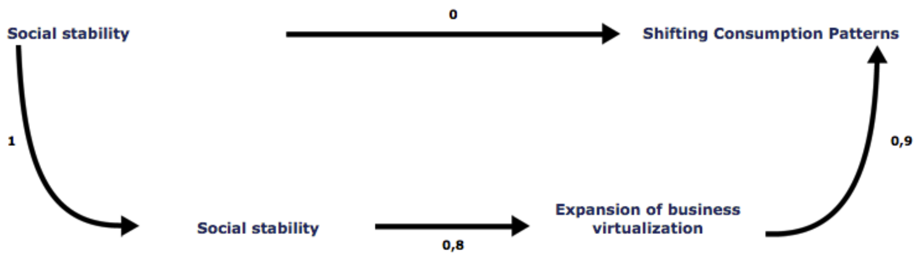


Fig. 11. Incidence variation (forgotten effect) between the Social stability cause and Shifting consumption patterns effect.

This incidence ratio demonstrates that, although initially an estimate of 0 was established in the Social stability incidence on Shifting consumption patterns, in reality, this ratio increases to 0.9 given that there is an interposed element (Expansion of business virtualization) potentiating and accumulating effects in the causality relationship. Fig 12 shows the total graph of incidences of the cause of Social stability on the effect of Shifting consumption patterns.

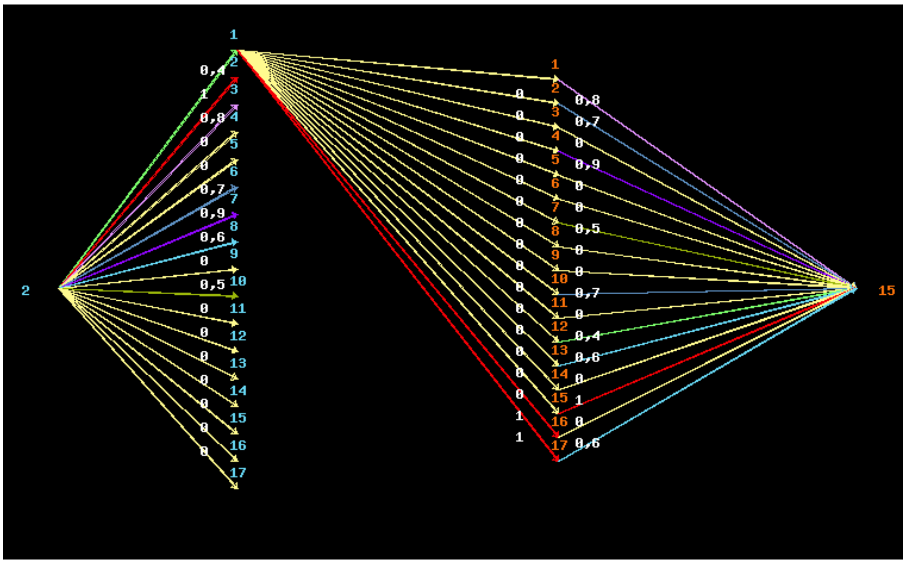


Fig. 12. Total graph of incidences of the cause Social stability on the effect Shifting consumption patterns.

Thirdly, Fig 13 displays the incidence variation between Political stability and Increased hygiene requirements (incidence C_3, E_{17}).

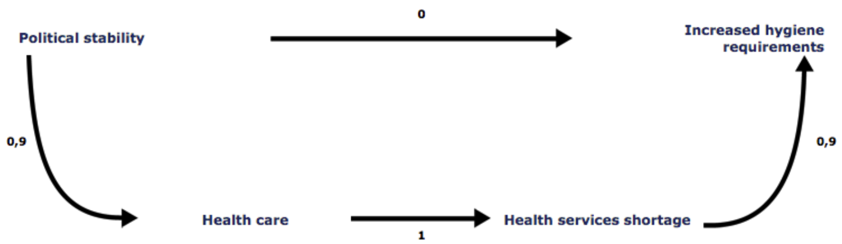


Fig. 13. Incidence variation (forgotten effect) between the Political stability cause and the Increased hygiene requirements effect.

This incidence ratio demonstrates that, although initially an estimate of 0 was established in the Political stability incidence on Increased hygiene requirements, in reality, this ratio increases to 0.9 given that there are interposed elements (Health care and Health services shortage) potentiating and accumulating effects in the causality relationship. Fig 14 shows the full graph of incidences of political stability on the effect of Increased hygiene requirements.

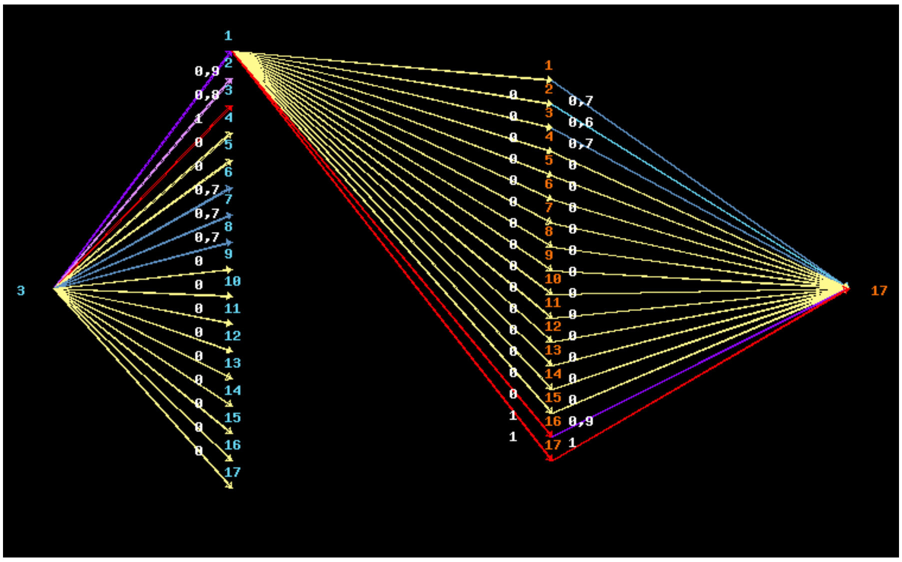


Fig. 14. Full graph of incidences of the cause Political stability on the effect Increased hygiene requirements.

Fourthly, Fig 15 displays the incidence variation between Economic stability and Health services shortage (incidence C_6, E_{16}).

Fig. 15. Incidence variation (forgotten effect) between the Economic stability cause and the Health services shortage effect.

This incidence ratio demonstrates that, although initially an estimate of 0 was established in the Economic stability incidence on Health services shortage, in reality, this ratio increases to 1 given that there is an interposed element (Health care) potentiating and accumulating effects in the causality relationship. Fig 16 shows the total graph of incidences of the cause of Economic stability on the effect of Health services shortage.

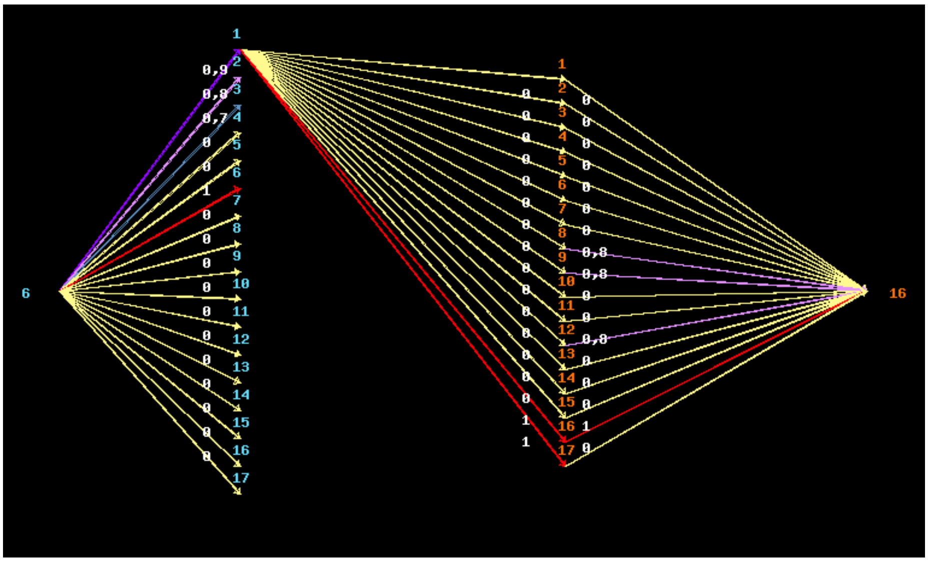


Fig. 16. Total graph of incidences of the cause Economic stability on the effect Health services shortage.

Fifth, Fig 17 shows the incidence variation between the Social justice and Shifting consumption patterns (incidence C_7, E_{15}).

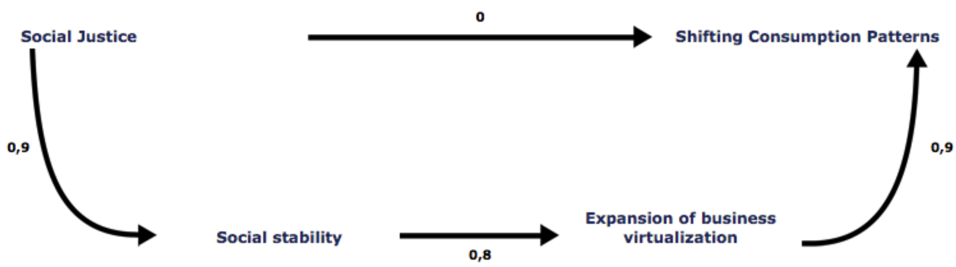


Fig. 17. Incidence variation (forgotten effect) between the Social justice cause and the Shifting consumption patterns effect.

This incidence ratio indicates that, although initially an estimate of 0 was established in the Social justice incidence on Shifting consumption patterns, in reality, this ratio increases to 0.9 given that there are interposed elements (Social stability and Expansion of business virtualization) potentiating and accumulating effects in the causality relationship. Fig 18 shows the total graph of incidences of the cause of Social justice on the effect of Shifting consumption patterns.

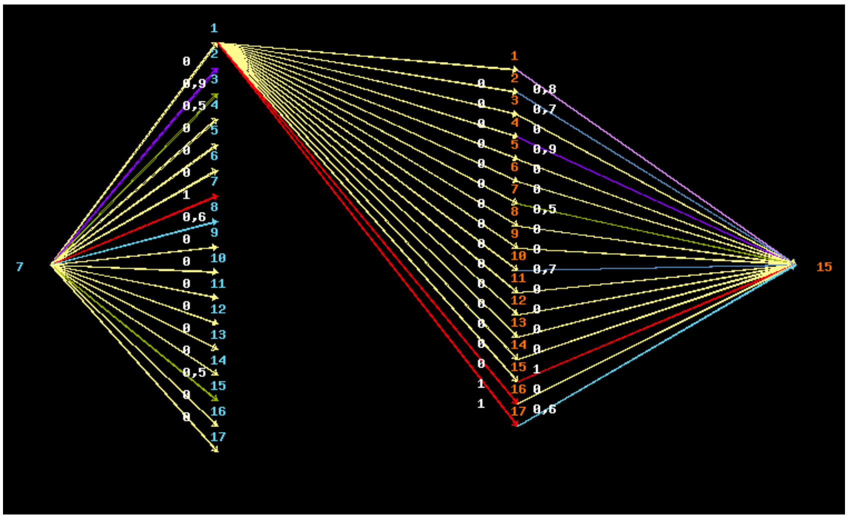


Fig. 18. Full incident graph of the Social justice cause on the Shifting consumption patterns effect.

Finally, Fig 19 displays the incidence variation between Level of corruption and Mental distress (incidence C_9, E_{11}).

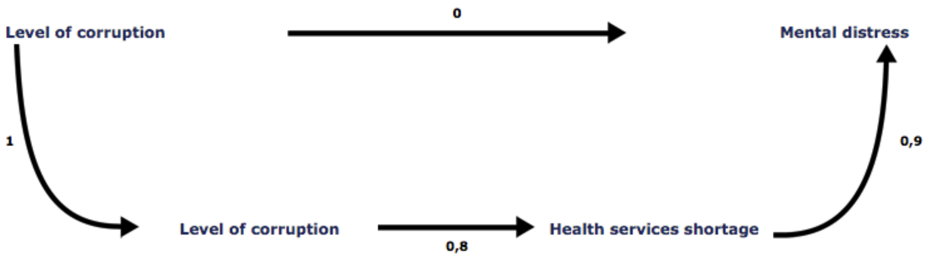


Fig. 19. Incidence variation (forgotten effect) between the Level of corruption cause and the Mental distress effect.

This incidence ratio demonstrates that, although initially an estimate of 0 was established in the Level of corruption incidence on Mental distress, in reality, this ratio increases to 0.9 given that there is an interposed element (Health services shortage) potentiating and accumulating effects in the causality relationship. Fig 20 shows the full graph of incidences of the cause of Level of corruption on the effect of Mental distress.

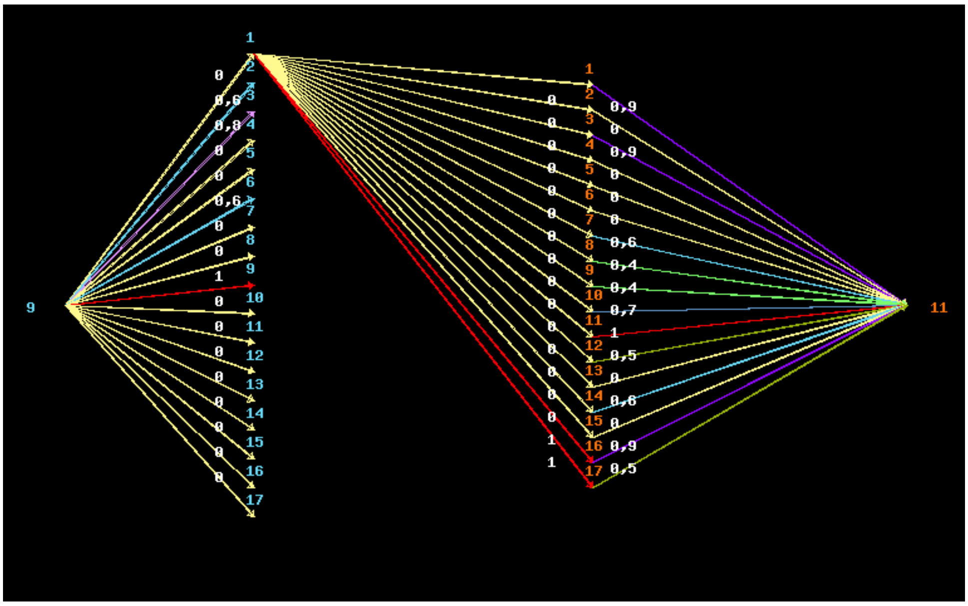


Fig. 20. Full graph of incidences of the cause Level of corruption on the effect Mental distress.

In summary, the study results highlight four main effects of the COVID-19 pandemic, including mental distress, changed consumption patterns, reduced health services, and increased hygiene requirements, which are supported by the findings of other studies [15]–[17], [19], [20]. The algorithm indicated that these effects are associated with causes, such as health care, social, political, and economic stability, social justice, and level of corruption, which supports the contributions of other research [1]–[3]. Applied research confirmed interposed elements that enhance and accumulate effects on causal relationships [26]. Therefore, the results are allowed to identify the forgotten effects, which contributes to predict and act more effectively on the causes, thus minimizing the effects. Finally, it should be noted that other effects were identified in this study, such as socioeconomic and environmental, as indicated in another research [18].

Conclusion

This research sought through literature review to promote awareness of increased uncertainty and negative impacts affecting decision-making. The study also indicated how fuzzy logic could help reduce risks by facilitating decision-making by understanding the forgotten effects of the pandemic on society. The results indicated that the world was already going through frequent and intense changes in social, economic, political, health, and environmental spheres. The pandemic caused by COVID-19 exposed unresolved structural problems and increased the crisis and, which potentiated global consequences, never before seen by humanity.

Therefore, the subject studied is broad and complex since multiple factors, directly and indirectly, influence the management of the crisis. The methodology of the forgotten effects allowed identifying some elements that are not readily observable and can impact society. Also, the algorithm helps the management of uncertainty and facilitates preventive decision-making.

The most critical limitation refers to the number of causes and effects included in the analysis, which means that the results cannot be generalized more broadly. The main contribution is to show the usefulness of an algorithm that identifies forgotten effects and prevents future crises. It showed that combining the different elements that form a direct or indirect part of the social context affects decision-making. Failure to consider forgotten or indirect causal relationships can lead to irreversible errors. The results allow us to predict and act more effectively on the causes, thus minimizing the crisis's effects on society.

This manuscript brings a significant contribution that will support future research lines in incidence matrices and the application of the methodology of recovery of forgotten effects on the socio-economic and health management of pandemic. Future research could include studies on the effects of climate change and nations' sustainable development following the end of the Covid-19 pandemic.

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