Causality: Intelligent Valuation Models in the Digital Economy

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Abstract: The study of the economic process can be presented as a chain of reflections on the causes and consequences of the particular phenomenon's occurrence, within the framework of which scientists try to study and understand the nature of cause-and-effect relationships and find out the mechanisms of their occurrence. This article discusses three well-known conceptual approaches to the assessment of causation in socioeconomic sciences: successionist causation, configurational causation, and generative causation. The author gives his own interpretation of these approaches, constructs graphic interpretations, and also offers such concepts as a linear sequence of factors, the causal field, and the causal space of factors in the economy and socioeconomic processes. Within the framework of these approaches, the development trends of these and new models are formulated, taking into account the transition of the world economy to a digital format. The article contains specific examples from the author of the causality models' implementation in scientific research related to assessing the impact of corporate culture on the main indicators of an organization's performance in various contexts.

Keywords: causality; digital economy; sequence of reasons; configuration of reasons; generalization of reasons; causal field; causal space

1. Introduction

The issues of causality's assessment of relationships in economics are discussed in a wide range of scientific areas, including philosophy, psychology, economics, management, physics, and chemistry. It is quite obvious that the mechanisms of the emergence of cause-and-effect relationships are universal in relation to the subject and object of research. In socioeconomic sciences, the issues of causality are identified with the new term causality, which is gaining popularity. Causality (Latin causalis) is the causal interdependence of events in time [1]. The variety of an application's spheres of the causality's concept determines the diversity of approaches to its study [2–17].

Experimental and quasi-experimental methods have become the basis of research practice in the field of searching for the causality of connections in economics, which made it possible to make a real revolution of reliability [2] in the field of empirical socioeconomic research. New methods and approaches, which have gone far beyond the scope of econometric and correlation–regression analysis, have made it possible to ensure high quality quantitative estimates are obtained and to reliably identify the presence of causal links in various socioeconomic processes. At the same time, a properly constructed design for experimental research is the key to a successful study of causality in economics.

The effectiveness of the causality's study in economics, based on a well-built design, was confirmed by Christopher Sims and Thomas Sargent, laureates of the Nobel Prize in Economics for 2011, awarded "for empirical studies of causality in macroeconomics" [13,14]. These scholars have developed methods

to answer questions about the causal relationship between economic policy and various macroeconomic variables such as GDP, inflation, unemployment, and investment.

When assessing causality in economics and socioeconomic processes in modern science, there are three main approaches to the study of cause-and-effect relationships.

The successionist causation approach explores and identifies vital elements of causality, such as variables or methods that describe socioeconomic processes. At the same time, research is aimed at observing the relationship between such variables using survey methods, tests, and experiments. The explanation of causality is based on the differences in associative links (real or false, direct or indirect), as well as on the assessment of the strength and significance of these links. [2,3,5,12–14,18,19].

The configurational causation approach implies the study of the socioeconomic process based on the comparison or comparative analysis of data. This means that research begins with the study of some cases of a set of socioeconomic processes or phenomena that have similarities and differences. The purpose of such studies is to find causality based on the selection of two sets of factors or parameters, some of which lead to similarity and others to difference. Thus, causality is the basis for dividing the studied set of socioeconomic processes into two clusters. As a result of the research, the key configurations of attributes are revealed, which make it possible to explain the differences in the conclusion for the entire set of considered socioeconomic processes [18–23].

The generative causation approach also begins by looking at measurable patterns that describe socioeconomic processes. However, it is assumed that they are caused by the action of some deep mechanism that describes human actions and, in general, is not formalized in the form of a set of variables or attributes. Causality, in this case, is reduced to the creation of behavior patterns in a broad sense [23–28].

The three presented scientific approaches are the basis of most scientific research aimed at elucidating causal relationships in the economy and socioeconomic processes.

The three scientific approaches described above transformed with the transition to a digital economy, since a completely different data analysis toolkit appeared. This was not only due to the development of tools for data analysis, cloud systems, and mining technologies, but also due to a significant increase in the data itself, the organization of accumulation, storage, and use in the study of various economic processes.

The purpose of this article is to propose a formalization of causality models within the framework of the three approaches discussed above, to assess their transformation in the digital economy, and to show examples of evaluating causality in economics based on one of the intellectual methods: fuzzy logic.

2. Causality in Economics and Socioeconomic Processes

The issues of model conceptualization of causality at the initial development stages were devoted to the work of a fairly large number of scientists, philosophers, and psychologists.

J. Mill [12] substantiated the principles of scientific knowledge and developed several conceptual models for detecting causes and effects in the study of socioeconomic processes (and beyond). He identified the understanding of the cause, using the logical interpretation of cause as a necessary and sufficient condition of the effect, and also suggested using the model of differences to identify causality. The essence of this model was to sift the factors of the studied processes through the sieve of the criterion, which was associated with an assessment of the change's collinearity in the premise and the result.

The second most important conceptual model of connection causality was developed by the psychologist D. Yum [29]. The basic characteristic of this model is associations, which the scientist defined as the ability to establish connections between sensations. Associations structure sensations according to the parameters of similarity and spatio-temporal extent. D. Yum defined the conditions for the emergence of the causality's association as follows: cause and effect must be adjacent to each other in time and space, the cause must precede the effect, and this connection must be necessary.

Thus, thanks to the conceptual models proposed in philosophy and psychology, the main factors influencing the assessment of the causal structure of processes and phenomena include the following: statistical connections between events, the temporal order of events following each other, a change in the natural course of events as a result of different events, and apriori representations and installations.

The metric evaluating such combinations of occurrence or absence of event occurrence can be determined on the basis of the conceptual models' classical formalization, that being the conjugation's equation of cause and effect: $\Delta p = p\,(Y|X) - p\,(Y|\neg X)$. In this equation, the degree of conjugation (Δp) is defined as the difference (according to J. Mill) of the consequence's conditional probabilities Y in the presence and absence of factor X. Let us pay attention to the fact that such formalization does not reflect the direction of the causal connection (from cause to effect), which is important in assessing causality [7,10,15,17].

Using the approaches discussed above, researchers are trying to solve some problems in assessing the causality of relationships between factors, in particular the problem of the direct influence of *X* on *Y*, the problem of delayed or retrospective causality, the problem of functionality (deterministic or probabilistic), the problem of causality of relationships, and many others [2–17].

The three approaches described above can be formalized as 1D, 2D and 3D conceptual models and presented as graphs (see Table 1).

Table 1. Conceptual models of causality in economics.

A Type of Causality's Conceptual Model in Economics	The Essence of the Causality's Conceptual Model in Economics
Successionist causation, with a graph of the sequential causation of factors in economics and socioeconomic processes.	The conceptual model of successionist causation is a 1D model (sequence) of variables describing the socioeconomic process and explaining the result. Causality is explored by incrementally adding variables, collecting data, creating measurement tools, and providing opportunities for processing experimental data. At the same time, the assessment of causality is based on a deep analysis of data associated with the search for effective combinations of variables' arrays that most accurately describe the socioeconomic process.
Configurational causation, with a graph of the configurational causation of factors in economics and socioeconomic processes.	The configurational causation conceptual model is a 2D model (configuration) that considers causation in the form of attributes' configurations (a variable or several independent variables) in a coherent system. The configuration analysis of causality in economics evaluates the outcome based on their combination of variables, which are commonly called attributes.
Generative causation, with a graph of factors' generative causality in economics and socioeconomic processes	The conceptual model of generative causation is a 3D model (generative) that explores causal relationships at the level of the mechanism of their occurrence and functioning in the economy. The connections' causality in economics is explained by the fact that the mechanism (*M*), acting in the context (*C*), will generate the result (*O*). These C-M-O technology offerings are the starting point and end product of research.

2.1. Successionist Causation

In the successionist causation (Figure 1) approach (1D model), the author establishes causal links between variables that explain the cause within a specific economic model describing a socioeconomic process, while identifying a sequence of causes to avoid the conclusion that everything causes everything and focus on finding really meaningful influences. This is mainly done in two ways.
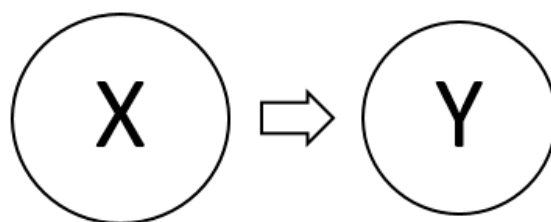
Figure 1. Successionist causation, with a graph of the sequential causation of factors in economics and socioeconomic processes.

The first method is to isolate critical causal relationships by manipulating data that are randomly divided into test and control samples. In this case, all but one of the variables are fixed, and thus the strength of the influence of this variable on the result is determined. Since the samples are identical in composition, only this variable can affect the result. Thus, the direct influence of the highlighted variable on the result can be observed and measured directly.

The second way to identify causality implies a similar logic, but the author achieves control of the result differently. To examine the veracity and strength of any particular causal relationship, a test variable is introduced. The author tests this variable to see if the original influence model has changed. In other words, the strength of this variable's influence on the result and the original variable is checked.

2.2. Configurational Causation

The configurational causation approach to identifying the causality of relationships in socioeconomic processes is based on the ideas of John Stuart Mill and his followers [12,20,21]. From a technical point of view, this is associated with the transition from a methodology based on variables to a methodology based on specific (particular) cases, in which attributes or conditions that are identified through data collection are considered. The difference lies in the fact that the author considers attributes as interrelated parts of the socioeconomic process, representing independent variables or sets of independent variables.

To clarify the meaning of this approach, let us give the example of Moore's study [19], in which the early industrialization of Britain was caused by such factors as a weak aristocracy, technological progress, a strong middle class, the movement of cheap labor, and the presence of colonies. Any of these factors apart from each other would be unlikely to cause changes in industrial production. However, taken together, these factors provide a powerful boost. Indeed, technological progress will not scale production without an influx of cheap labor, which is possible through the presence of colonies. Thus, the + sign in Figure 2 means the presence of a certain set of attributes. Understanding the attribute as a set of interrelated variables, we get the first fundamental feature of the second approach. It is the combinatorial nature of the attribute structure that is the key characteristic of causal complexity, which the author considers in the second approach. The second important point in understanding the meaning of configurational causality is that it is comparable phenomena that are compared in the search for causality. Thus, in the example of the early industrialization of Britain, a comparative analysis of attributes' similar structures in the industrialized countries of that period (France and Germany) would give us an answer to the question of why Britain became the leader of industrialization at that time.

Within the framework of the second approach, technology for identifying causal relationships was developed, which was called qualitative comparative analysis [21,22].
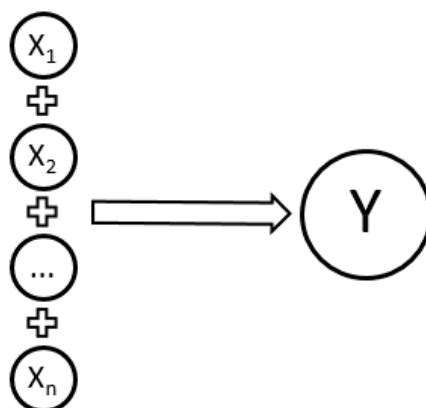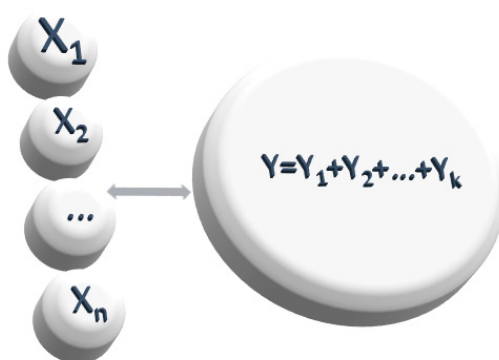
Figure 2. Configurational causation, with a graph of the configurational causation of factors in economics and socioeconomic processes.

2.3. Generative Causation

The generative causation approach is based on an ordered sequence of applying rules to a set of abstract symbols [1]. Issues related to the emergence and development of this approach have philosophical roots and are associated with the concepts of critical realism [25–28] and generative modeling [30–33].

The first fundamental difference of this approach lies in the different presentation of the research results. In generative explanation, the goal is to explain what causes causal relationships; that is, the goal is to identify some patterns of relationships between attributes and outcomes in the form of association rules. A set of such patterns can be considered as possible patterns of behavior in the study of socioeconomic processes. In essence, the presentation of the result is also understood as a collection of attributes, and the causal arrow is replaced with an equivalence sign (double-headed arrow) (Figure 3), which shows the relationship of variables' sets. Thus, in the generative approach, the results are the object of explanation, since they describe more complex sequences, comparisons, trends, and relationships.

Figure 3. Generative causation, with a graph of factors' generative causality in economics and socioeconomic processes.

The second difference is generative mechanisms, or underlying mechanisms, which reflect the uniqueness of the approach and explain the patterns of results. Causal relationships, in this case, are in the mechanism of action of causality and are understood as potentials or processes inherent in the system under study. Thus, socioeconomic research begins with templates of results and with the hypothesis about the choice and argumentation of attributes.

The third difference concerns the contexts that are needed to explain the typology of the results. The contexts represent the possible options in the generative explanation of causal links. The contexts are pre-existing institutional, organizational, and social conditions that define the framework for the

study of causality in the socioeconomic process. They allow one to develop an infrastructure for the study of causality in socioeconomic processes.

The research begins with hypotheses aimed at explaining a pattern of outcomes by postulating how they can be explained within a specific context. Then, the author carries out empirical research to understand better the setting of an action's mechanism as part of an iterative process of correlating inputs and outputs.

An example of generative causality can be found in the discoveries of Nobel laureates in the field of economics, who proceed by building their models from some causal assumptions, obtaining new economic laws, and generalizing traditional economic laws. J. Akerloff argues that rational behavior in different market segments should take into account a certain degree of information asymmetry between the seller and the buyer [34]. Thus, to study the effectiveness of market behavior (according to Pareto), it is proposed to add the attribute of information asymmetry. At the same time, the result in such a causal space turns out to be multivalued, since the asymmetry attribute for different categories of market agents describes the real market situation in different ways. Generative causation in this sense gives rise to a new theory of market behavior. The context, in this case, may be a specific market in which the above causal space of factors is considered, such as the used cars market, insurance, the medical market, and others.

2.4. Comparative Analysis of Conceptual Models of Causality

Within the framework of the first two approaches, researchers focus on finding and applying appropriate methods and tools to perform basic calculations that assess the strength and quality of communication, since these characteristics are fundamental for constructing the causality mechanism, which is described in the third approach. However, in the first two approaches, research has not focused on the question of why the individual partial causalities of variables and attributes make sense. This means that the variables and attributes, as well as their interrelationships, are responsible for establishing the strength of the causal relationship, but they do not take into account the infrastructure and context of the considered socioeconomic process, even though these characteristics structure what is happening and affect the quality of the research. In other words, the first approach (sequence of causes), which can be conventionally called linear (one-dimensional model, or 1D), can be improved by adding variables, but adding such element-by-element complexity leads to an increase (exponentially) in computational and descriptive complexity. The second approach (configuration of causes) takes into account the relationships between variables and allows them to be represented as attributes. Applying the provisions of this approach, we can argue that we are dealing with a causal field of factors and attributes (two-dimensional model, or 2D). To improve research results in this approach, the author used additional comparisons, which also led to an increase in the complexity of the model for assessing the relationships' causality. Within the framework of these two approaches, it is rather difficult to obtain stable, empirical generalizations and explanatory persuasiveness.

The third approach, a generalization of causes (three-dimensional model, or 3D), has the best technology for assessing the causality of relationships in socioeconomic processes, since it contains elements that allow the strengthening of generative reasoning. However, just because context–mechanism–result configurations provide more explanatory flexibility than variable or attribute-based models does not mean that they are in any way final or complete. Of course, the mechanisms' formation of relationship causality requires a more powerful data set and complex assessment methods. At the same time, the presence of context makes it possible to strengthen the explanatory nature of causality in socioeconomic processes, and the causal space of factors makes it possible to transfer the constructed mechanism from one area to another with minimal losses.

3. Mathematical and Instrumental Models of Causality in the Digital Economy

In mathematics, there are three well-known theories which are engaged in modeling socioeconomic processes under conditions of uncertainty: the probability theory, the theory of possibilities, and the theory of fuzzy sets.

The probabilistic-statistical, fuzzy, and expert methods and models are considered as fundamental economic and mathematical models of the causality of relationships between factors, implying the study of the occurrence of events within the framework of the experiments while taking into account the design of the experimental research [35–37].

Speaking about the features of each method, we should pay attention to the algorithms of expert assessments that answer the following question: how is the opinion of an expert or a group of experts processed? Among these algorithms, at least two groups can be distinguished: algorithms for quantitative assessments and algorithms for qualitative assessments. The most common methods of expert relationship causality assessment are methods that allow one to evaluate various coefficients of causal relationships between factors of socioeconomic processes: decision making trial and evaluation laboratory (DEMATEL) [38–40], matrix d'impacts croises multiplication appliqué un classement (MICMAC) [41–44], and a method for detecting and assessing the influence of implicit factors [45–48].

The DEMATEL method [38–40] is one of many multicriteria decision-making methods that implies the effective identification of causal relationships of a complex system based on the aggregation of expert assessments. This method aggregates the collective expert opinion to exclude random relationships between indicators and criteria and, based on causal links, identify the most important indicators that determine the integral characteristic. The method allows for the determination of direct, reverse, and indirect relationships, as well as the direction of the interdependence between the criteria and indicators.

The MICMAC method [44] stands for matrix d'impacts croises multiplication appliqué un classement, which literally means a composition of the cross matrix and classification. The analysis using this method is a procedure for constructing a classification matrix of the factors' cross-influence and is intended to assess the degree of dependence of the variables' influence (the strength of causal links) based on ranking. Each of the studied factors belongs to one of four clusters: autonomous, dependent, interrelated, and independent. These factors (drivers) are grouped based on a specific potential and strength of influence. Autonomous factors (quadrant 1) are factors that have weak potential and low influence. As a rule, they are practically insignificant in determining causality. Dependent factors (quadrant 2) are factors that have a low potential but strong influence. Interrelated factors (quadrant 3) are factors that have high potential and the power to influence. These factors are causally related, which means that an action on one of them will lead to a change in the other. Independent factors (quadrant 4) are factors that have strong potential but little impact. All factors are plotted on a four-cluster graph, where the potential of the variable is on the *Y*-axis and the force of influence is on the *X*-axis.

In [45–48], a pool of economic and mathematical models was proposed that allowed, on the study's basis of organizational management factor variety, to single out implicit ones. After this, based on the apparatus of fuzzy logic and using Gauguin's implication, the influence's degree of these factors on the management of other factors can be assessed. As an example, it is proposed to assess the impact of corporate culture on the main indicators of an organization's performance. At the same time, using fuzzy binary relations, it is possible to obtain a causal field of factors that determine the causal relationship between corporate culture and the main indicators of the organization's activities.

Modern digital technologies make it possible to receive and process large amounts of data in real time. This makes it possible to widely use the arsenal of mathematical theories and methods associated with probabilistic, statistical, and expert assessments of various determinants of socioeconomic processes.

Accordingly, there are at least three main trends that will allow a revolution of reliability in causal studies of economies and socioeconomic processes and improve the quality of their management.

The first trend is associated with the development of existing expert methods based on the aggregation of estimates obtained using big data processing technologies. This trend implies the development within the framework of all three approaches to assess causality; however, it most clearly codifies the first two approaches: the sequence of causes and the configuration of causes. Indeed, the methods of data mining, firstly, are not afraid of multiple increases in variables in causal models of the study of socioeconomic processes. This means that using the available tools (e.g., SAP Analytics Cloud, SAP HANA, Power BI, QlikView, Phyton, and R), the researcher, given the data, can perform multiple types of checks on various factors for causality and increase the reliability of the result. Secondly, given the availability of data, it is possible to build algorithms for formalizing quantitative estimates (for example, ranking factors) that will partially or completely replace expert opinion. Additionally, the use of fuzzy control technologies as an intelligent method of data processing will give a rather tangible effect on the development of the digital economy.

The second trend is associated with the use of intelligent data processing algorithms that can be configured to measure the causality of fields and factor spaces. This trend will significantly formalize the approach of generalization of causes and make it accessible to most researchers. Note that the generalization of causes implies the construction of associations and classifications (according to D. Hume and J. Mill). Within the framework of existing algorithms, the author would like to pay attention to two main methods: the algorithm for constructing Bayesian networks and the apriori algorithm which, based on specially prepared data sets, allow us to construct association rules characterizing the behavioral characteristics of people, the participants of socioeconomic processes.

Over the past twenty years, Bayesian networks have become one of the basic tools for formalizing uncertainties in artificial intelligence. Bayesian networks not only provide a natural and compact way to encode the factors of exponential size in causal space, but also give efficient probabilistic inference in real time [49–52]. It is important that Bayesian networks are directed acyclic graphs, where nodes are random variables and edges are conditional relationships between random variables, distributed either discretely or continuously, since most of the structural and functional models of socioeconomic processes are presented in the form of various hierarchies (acyclic graph).

The third trend is related to machine learning algorithms and methods. Due to the flexibility of settings and instrumental support, these algorithms allow, within the framework of any of the above approaches, for the development of new methods and technologies for assessing causal links in socioeconomic processes that are not known today.

4. Fuzzy Model of Generative Causality in Economics and Socioeconomic Processes

Generative causality of relations in economics implies the use and formalization of three components: the mechanism (M), the context (C), and the result (O), as well as the presence of attributes and conditions described using variables of the economic process under consideration (X).

During the experiment to assess the causality of the connections, the researcher tests the hypothesis, which is formulated in terms of if–then. In the algebra of logic, this is called implication. Classical logic is strictly binary and is based on the concepts of truth and false, which are mutually exclusive. At the same time, real implications in the if–then format are not so categorical. Modeling economic processes in this regard is no exception. Therefore, the process of formalizing implications is based on multivalued logic, and a large number of studies use fuzzy logic in particular.

Models based on fuzzy logic have some basic differences from traditional optimization models that allow them to achieve a certain competitive advantage:

- Use of fuzzy numbers, which represent interval values (a number of parameters in any models cannot be set unambiguously, including expert opinions and marketing survey results);
- Formalization of natural language words using the apparatus of linguistic variables (e.g., better, worse, and possible);
- Conducting qualitative assessments of the initial data and results, according to the degree of their reliability, taking into account the interpretation in the words of the natural language;

- Modeling complex economic processes and systems with a given degree of accuracy based on fuzzy logic methods (the researcher does not spend a lot of time finding out the exact values of variables and drawing up regression equations).

Fuzzy logic basics are based on the standard logical operations of Boolean algebra: AND, OR, and NOT. They are specified using T-norms (triangular norm) and T-conorms.

The fuzzy logic is based on the fuzzy inference procedure. A fuzzy proposition is defined as a statement like *p*: *x* is *A*. The *x* symbol denotes a characteristic of the process. The *A* symbol denotes a linguistic variable associated with a fuzzy set, and the *p* symbol is an abbreviation for the proposition. Fuzzy sentences are combined with each other by AND or OR, which are realized using T- and S-norms. They are called conditions or prerequisites, and the indicator if is used for them.

The set of conditions determines the conclusions' set or conclusions; the indicator then or that is used to indicate them. The set of conditions and conclusions defines the production fuzzy rule:

$R1$: if $x1 = A11$ and $x2 = A12 \ldots$ then $y1 = B11$ and $y2 = B12$ and $\ldots$
Or $\ldots$
A set of fuzzy production rules form a fuzzy rule base $\{Ri\}|i = 1 \ldots k$.
There are three stages of information processing:

1. Conversion of an input physical variable into a fuzzy set, which is a fuzzyfication procedure;
2. Logical processing of fuzzy variables (composition, implication) of the rule base, obtaining local inferences from the rule base, and aggregating the general inference in the form of a fuzzy set;
3. Transformation of a fuzzy set into a result, or defuzzyfication.

To model generative causality, we will use the apparatus of the fuzzy sets theory.

Let *X* be a fuzzy set characterizing the attributes of a socioeconomic process, *C* be a fuzzy set characterizing the contexts of the studied mechanism of the socioeconomic process, *O* be a fuzzy set characterizing the investigated result of the socioeconomic process, and *M* be a mechanism for assessing the links' causality of the socioeconomic process.

The general plan for constructing the mechanism *M* of generative causality falls into two stages:
First stage:
construction of a fuzzy set *X*;
construction of a fuzzy set *C*;
construction of a fuzzy set *O*.
Second stage: construction of a generative causality's model, its study, and solution of the task.
The sequence of the first stage's operations:

- Primary definition of a set of numerical (measurable) indicators for the construction of each of three fuzzy sets;
- Lists of numeric indicators' sets.
- Sequence of the second stage's operations:
- Assessment of the indicators' mutual influence in pairs: (*X*, *C*), (*C*, *O*), (*X*, *O*);
- Interpretation of the results obtained.

The sets *X*, *C*, and *O* are represented by the values' sets of indicators:

$$X = \{x_1, x_2, \ldots x_n\}$$

$$C = \{c_1, c_2, \ldots c_m\}$$

$$O = \{o_1, o_2, \ldots o_k\}$$

In this problem, we are interested in fuzzy binary relations:

$$x \, \rho_1 \, c : x \, affects \, c, \; (x, c) \in X \times C,$$

$$c \, \rho_2 o : c \; affects \; o, \; (c,o) \in C \times O,$$

$$(1)x \, \rho_3 \, o : x \; affects \; o, \; (x,o) \in X \times O$$

In the first stage, the conversion of data to fuzzy form consists of representing the values' sets of indicators in the form of a fuzzy set with the property of subnormality. This is done with the following transformation:

$$
\begin{aligned}
a_i &= \frac{x_i}{\max_i x_i}, \quad i = 1..n \\
b_i &= \frac{c_i}{\max_i c_i}, \quad i = 1..m \\
d_i &= \frac{o_i}{\max_i o_i}, \quad i = 1..k
\end{aligned}
\tag{1}
$$

As a result of such a transformation, information about the specific values of an element of the set is lost, but information about their ordinal value and relationship is retained, which means that the essence of the model does not change. This allows us to represent our initial data for each set of values in the form of a fuzzy set of a discrete type and write it down in the form of the following singletons:

$$
\begin{aligned}
X &= \sum_{i=1}^{n} a_i / x_i \quad i = 1..n \\
C &= \sum_{i=1}^{n} b_i / c_i \quad i = 1..m \\
O &= \sum_{i=1}^{n} d_i / o_i \quad i = 1..k
\end{aligned}
\tag{2}
$$

To assess the influence of the components of the sets X, C, and O, we use the theory's apparatus of fuzzy binary relations.

In the second stage, fuzzy control technologies offer a tool based on the procedure of fuzzy implications, which is implemented in the format if–then and has several modifications [20,21]. In particular, in practice, fuzzy inference (implication), according to Zade, Gauguin, Mamdani, Lukasiewicz, and Wadi among others, is used. Taking into account our problem, it will look like this. We estimate the influence of the predictor on the final result using the Gauguin fuzzy implication formula.

If the value $x_i = a_i$, then the value $c_i = b_j$, where $i = 1..n$ and $j = 1..m$. The truth of this statement is determined by the Gauguin rule. The true value will be denoted by s_{ij}, $J_{XC}-$. It is a matrix that characterizes the strength of the relationship between the variables of the set X and the set that characterizes the context of studying the relationships' causality in socioeconomic processes and economics:

$$J_{XC} = \left\{ s_{ij} = \left(1, \frac{c_j}{a_i} \right) \right\} \tag{3}$$

This approach will allow us to estimate the influence of each element of the fuzzy set X on each element of the set C. Similarly, we obtain the matrix J_{CO} :

$$J_{CO} = \left\{ u_{ij} = \left(1, \frac{o_j}{c_i} \right) \right\} \quad i = 1..m, \; j = 1..k \tag{4}$$

The cumulative influence of an element a_i on o_j is taken as equal to the maximum of indirect influences through all elements of the context, formalized as a fuzzy set C:

$$z_{ij} = \left(\left(s_{ip}, u_{pj} \right) \right) \quad i = 1..n, \; p = 1..m, \; j = 1..k \tag{5}$$

Considering the operation min as multiplication and max as addition, we obtain that all influences of X on O, mediated through the context C, are determined by the product of matrices J_{XC} and J_{CO}:

$$J_{XO} = J_{XC} \circ J_{CO} = \begin{pmatrix} z_{11} & z_{12} & \dots & z_{1k} \\ z_{21} & z_{22} & \dots & z_{2k} \\ \dots & \dots & \dots & \dots \\ z_{n1} & z_{n2} & \dots & z_{nk} \end{pmatrix} \qquad (6)$$

The constructed general model allows one to find and evaluate the influence's strength of the indicators of the set X on the indicators of the set O through the context C. The estimates of this influence are the elements of the matrix J_{CO}.

In order to clarify this influence, insignificant influences can be discarded. For this, we can set the threshold value α:

$$\begin{aligned} l_1 &= \left(z_{ij} \right) \\ l_2 &= \left(z_{ij} \right) \\ \alpha &= max(l_1, l_2) \end{aligned} \qquad (7)$$

With these values, then

$$z_{ij} = \begin{cases} z_{ij}, z_{ij} \geq \alpha \\ 0, z_{ij} < \alpha \end{cases} \qquad (8)$$

The resulting model is universal for any context C. This means that by changing the values of the context (elements of the set C and their number), one can obtain other communication matrices and assess the causality of the input and output elements of the socioeconomic process using different contexts. Indeed, by setting $C^* = \{c_1{}^*, c_2{}^*, \dots c_t{}^*\}$ and repeating the procedure given by the sequence of the previously described stages, we obtain a new connection matrix:

$$J_{XO}^* = \left(z_{ij}^* = \left\{ z_{ij}^*, z_{ij}^* \geq \alpha \ \ 0, z_{ij}^* < \alpha \quad \right. \right) \qquad (9)$$

The developed model allows one to compare the influence of different contexts C on the causality of the input and output variables of the socioeconomic process. By setting an arbitrary comparison metric and the measurement error ε, one can conclude that the influence is causal, depending on the considered context C based on the following criterion:

If $J_{XO} - J_{XO}^* \leq \varepsilon$, then the influence is considered insignificant; that is, it is considered independent of the context C. Otherwise, it is dependent.

In our case, we suggest using $\varepsilon = \alpha/10$. As a metric, the following expression can be used:

$$M = \| J_{XO} - J_{XO}^* \| = \left(\left| z_{ij}^* - z_{ij} \right| \right) \qquad (10)$$

Under the conditions of the described model, Equation (10), taking into account the criterion, formalizes the influence's mechanism of input and output indicators, indicating the importance of the context.

5. A Fuzzy Model's Application of Generative Causality to Assess the Impact of Corporate Culture on Key Performance Indicators of an Organization in the Consulting Center LLC SAP CIS, Yekaterinburg

The issue of assessing the causality of corporate culture, the sustainability of development, competitiveness, and performance indicators of organizations is relatively new and studied little in Russia and abroad. Then, the author, realizing the complexity of the phenomenon under consideration, made an attempt, in his own way, to explain the complex interaction of attributes and build various combinations, sorting them according to their importance. Based on the obtained configurations, a method for assessing the causality of corporate culture and the main indicators of the enterprise

(organization) was developed. However, there was no general model that would answer the question of how the change in corporate culture affects the results of the organization's activities. In [45–47], the author proposed one of these models. The disadvantage of the proposed model was that it did not take into account the various contexts of application of the assessment of causality of relationships. The proposed model corrects this shortcoming. The universal structure of the model makes it possible to test various contexts of causality of connections using the algorithm proposed by the author.

Based on the reflexive selection procedure, the causal space of factors was compiled, depending on the context, and the indicators were distributed over three sets in accordance with the model.

The corporate culture was assessed according to the method described in [53–55], using a tool developed by the author in the form of a cloud solution (http://bi.usue.ru/nauka/ocenka-implicitnyh-faktorov/). The context described in Table 2 is related to project management. Key performance indicators are fairly standard for any organization operating in a market environment. Let us compose a similar table in the context of sales management (see Table 3).

Table 2. The system of performance indicators of the consulting center LLC SAP CIS, Yekaterinburg for the model of generative causality in the context of project management.

Indicators of Corporate Culture (Set X)	Context (Set C)	Key Performance Indicators of OOO SAP CIS, Yekaterinburg (Set O).
x_1: ability to adapt x_2: mission x_3: collaboration x_4: engagement	c_1: share of smart solutions in projects c_2: share of projects without delays	o_1: net profit o_2: sales of products and services o_3: profitability

Table 3. The system of performance indicators of the consulting center LLC SAP CIS, Yekaterinburg for the model of generative causality in the context of sales management.

Indicators of Corporate Culture (Set X)	Context (Set C)	Key Performance Indicators of OOO SAP CIS, Yekaterinburg (Set O).
x_1: ability to adapt x_2: mission x_3: collaboration x_4: engagement	c_1: share of smart solutions sales c_2: Share of successful consulting for intelligent solutions support c_3: share of the revenue from each sale to the sales department	o_1: net profit o_2: sales of products and services o_3: profitability

Applying the stages of modeling described above in Equations (1)–(9), from the data of Tables 4 and 5, we obtain two matrices:

$$J_{XO} = \begin{pmatrix} 1 & 0.84 & 0.75 \\ 0 & 1 & 0 \\ 1 & 0 & 0.67 \\ 0.56 & 0 & 0.43 \end{pmatrix}$$

$$J_{XO}^{*} = \begin{pmatrix} 1 & 0.37 & 0 \\ 0.87 & 1 & 0 \\ 1 & 0.42 & 0.67 \\ 0.35 & 0 & 0 \end{pmatrix}$$

Substituting the results obtained in Equation (10) and taking into account that $\varepsilon = 0.05$ means that

$$M = 0.87 - 0.84 = 0.03$$

The result obtained allows us to substantiate the assumption that corporate culture is indeed causally related to the main indicators of the organization's performance, regardless of the context

in which its influence is considered, and its improvement will inevitably lead to an increase in the efficiency of the organization.

Table 4. Performance indicators of LLC SAP CIS in Yekaterinburg for May 2019.

Set	Index	Value
X	x_1 (points)	0.78
	x_2 (points)	0.78
	x_3 (points)	0.76
	x_4 (points)	0.75
C	c_1 (%)	15
	c_2 (%)	80
O	o_1 (rub.)	4,580,000
	o_2 (rub.)	8,923,000
	o_3 (rub.)	746,500

Table 5. Performance indicators of OOO SAP CIS in Yekaterinburg for May 2019.

Set	Index	Value
X	x_1 (points)	0.78
	x_2 (points)	0.78
	x_3 (points)	0.76
	x_4 (points)	0.75
C	c_1 (%)	52
	c_2 (%)	76
	c_3 (%)	48
O	o_1 (rub.)	4,580,000
	o_2 (rub.)	8,923,000
	o_3 (rub.)	746,500

6. Conclusions

Within the framework of the theoretical and methodological study of generally accepted approaches in economics, an attempt was made to build their models, based on a deep analysis of the content of this issue. It should be noted that there are clearly not enough publications in Russian science that use three main approaches to the study of cause-and-effect relationships, which include successionist causation, configurational causation, and generative causation. The digital format of the world's development allows one to go from conceptualizing causality directly to the applied use of the accumulated experience and knowledge in this area, using modern tools for analysis based on one of the methods of intellectual data analysis, particularly fuzzy logic. This approach will make it possible to more accurately identify the cause-and-effect relationships of economic processes and get better effects from research in this direction. The versatility of the considered fuzzy generative model for studying the influence of corporate culture on the main indicators of the organization's performance allows us to develop software in the future that will contribute to the development of research in the field of constructing applied digital models of causality in the economy.

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