

Article

# Reliability Evaluation of the Factors That Influenced COVID-19 Patients' Condition

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**Featured Application:** The classification problem is one of the problems often used in medical applications. The proposed method can be used to quantify the influence of the classification attributes on result of the classification.

**Abstract:** Health and safety is a problem that is intensively discussed nowadays. The failures in healthcare are called medical errors: if the patient's condition worsens or he/she contracts an illness, then the actions that led to this are interpreted as medical errors. Medical errors can be the result of new procedures, extremes of age, complex or urgent care, improper documentation, illegible handwriting, or patient actions. One of the ways to reduce medical error is an evaluation of its possibility, and then using the result of this evaluation to improve the medical organization units and processes in patient diagnosis, treatment, and care. This evaluation is possible based on methods of reliability engineering. The reliability engineering methods allow evaluating of different systems' reliability and the influence of external and internal factors on system reliability. These methods' application needs the system to be investigated or objective interpretation in terms of reliability engineering. Therefore, such a system in healthcare, for the diagnosis of disease, a patient's treatment, the influence of different factors on a patient's condition, and others, should be presented according to the rules and demands of reliability engineering. The first step is development of the mathematical representation of the investigated system or object according to the demands of the reliability analysis. One of the often-used mathematical representations in the reliability analysis of a system is the structure function. However, this mathematical representation needs completely specified initial data. The initial data from the healthcare domain for medical error analysis is uncertain and incompletely specified. Therefore, the development of this mathematical representation needs special methods. In this paper, a new method for the mathematical representation of system development based on uncertain and incompletely specified data is proposed. The system evaluation based on the structure function allows computing of many reliability indices and measures used in reliability engineering. The approbation of this method is considered based on an example of COVID-19 patients.

**Keywords:** reliability analysis; uncertain data; system reliability; classification; fuzzy classifier



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## 1. Introduction

Early studies in reliability engineering were mainly aimed at technical systems. The development of these studies has resulted in the extending of the conception of the subject of investigation in this area. At the present time, the methods and approaches of reliability engineering are used for analysis and evaluation of different system types (objects), which include human factors [1], maintainability [2], environmental factors [3], and social impact [4]. This has led to the application of reliability engineering in non-typical areas for risk and reliability analysis by these methods. One of these areas is healthcare.

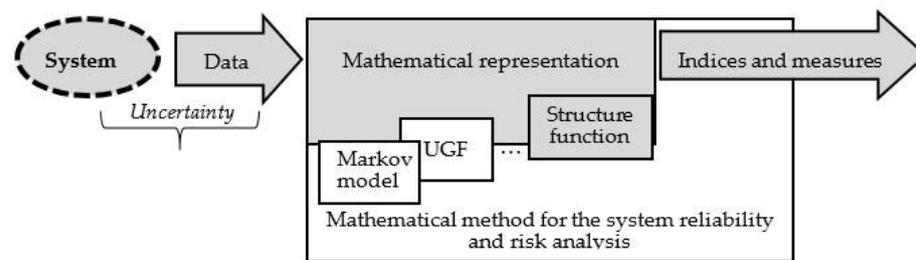
The studies of reliability and risk analysis in healthcare must improve the quality of patient care, reduce medical errors, and increase healthcare safety [5]. According to data in

one report [5], four out of ten patients experience medical errors in primary and outpatient care. The cost of medical errors is about US\$ 42 billion per year. The causes of medical error can be various, but most often they are resulted from technical [6], organizational [7], ergonomic [8], and psychological [9] factors. All of these factors in any part of the healthcare system must be taken into account and considered under the analysis of the conception of healthcare safety [5]. The coronavirus pandemic has exacerbated many problems regarding health and safety [10,11]. Timely analysis and evaluation of healthcare safety can help avoid complications for patients [12].

In recent years, two principal directions of studies in healthcare safety has been considered [1]. One of them is named “technical”. It is based on the usage of methods of reliability engineering [13–16]. The other direction is named “cognitive” and developed dominantly in the medical domain [7–9]. The studies regarding the “cognitive” direction is often based on an analysis of questionnaires [9]. In [9], such an analysis is implemented to consider some psychological factors (personality, morality, and ideology) in a community in the time of the COVID-19 pandemic. In this paper, the methods of the “technical” direction are considered. The first studies in healthcare safety have been presented in [17] for the reliability analysis of medical devices and in [18] for the Human Reliability Analysis (HRA) in medicine. These two directions of investigations of reliability engineering in medicine have been developing independently for a long time [6,8,19]. The intensive development of information technologies and their application in healthcare has caused a change in reliability engineering studies for medical applications [13,20]. New parts (components), such as the software [14], communication platform [15], organization factor [21], and others [22], have been included in the analysis of reliability of different healthcare systems. In the current investigation of reliability in the healthcare domain, the systems are complex and consist of heterogenous components and such systems in term of reliability engineering are interpreted as a socio-technical system [23]. One more specific of healthcare safety analysis and evaluation is the incomplete specification and uncertainty of the initial data [10,18]. These two specifics (complexity of the investigated system and uncertainty of the initial data) are the principal factors that cause the development of new methods for reliability analysis in healthcare safety. The studies of healthcare safety in time of the coronavirus pandemic are restricted by uncertainties and weak knowledge even more [10,11,24]. Therefore, the methods for reliability analysis that allow analysis and evaluation based on uncertain data should be considered as the first.

Reliability and risk analysis typically includes the forming of a mathematical representation of the investigated system, which allows calculating the indices and measures for the system reliability or risk evaluation (Figure 1) [25–27]. There are different types of mathematical representations of the system in reliability and risk analysis, which correlate with the mathematical methods used for the evaluation (calculation of the indices and measures). For example, the Markov model, Universal Generation Function (UGF), and structure function are most often used as the mathematical representations. The Markov model as mathematical representation and methods for its evaluation are effective in a time-dependent reliability analysis [28]. UGF-based methods are used if the basic processes of the system functioning are indicated [29]. The structure function is one of simplest and most often used mathematical representations introduced in reliability analysis, as one of the first in [30,31]. Important advantages of the system representation using the structure function can be summarized as follows [25,27]:

- the possibility of a time-dependent and time-independent reliability analysis;
- the univalent correlation of the system state and component states for all possible combinations of the components states;
- the canonical representation of the system with any structural complexity;
- the complexity of the system representation is not dependent on its structure complexity and depends on the number of components only.



**Figure 1.** The structure of the system reliability and risk analysis.

The disadvantage of the structure function as the mathematical representation is the possibility to be formed using completely specified data only. The structure function is defined as a function, which maps of all possible system components states to the system states. Therefore, all data about system functioning, degradation, and failure should be indicated. One of the problems of the structure function-based method application in healthcare is the inability to obtain complete information about the structure and behaviour of the systems. In healthcare, it is impossible to observe and collect information about all situations, because some of them can have a hazard to a patient's health. The data in this case is incompletely specified. In some situations, the absent information or data can be introduced based on expert knowledge. This information is ambiguous and unequal and can be evaluated with just some confidence. These facts cause that the initial data for the mathematical representation of a system in healthcare is uncertain and incompletely specified. This fact influences the step of the definition/construction mathematical model of the investigated system, in particular, the structure function [32–34]. There are studies pertaining to the reliability analysis of special cases such as healthcare systems, which are in a condition of uncertainty regarding the initial data; for example, safety of pacemaker application [20], surgical patient care [35], and expert knowledge collection in healthcare [36]. However, the proposed methods in these studies can be used for specified cases only. The development of a new method for the forming of the mathematical representation based on uncertain data, which can be used for a large number of systems, is a relevant problem in reliability and risk analysis in healthcare.

In this paper, we propose a new method for the structure function construction for the mathematical representation of a system based on incompletely specified and uncertain data, which can be used for different types of systems in healthcare. For example, uncertainty and incompleteness are typical for data related to coronavirus disease problems [10,11,37,38]. The important aspect of the proposed method is interpretation of the structure function as classifier, which divides all possible system states into several predefined classes (for example, fault states and working states) [25,33]. This interpretation allows us to consider the structure function construction as the classification problem of incompletely specified and uncertain data. This problem is typical for Data Mining. There are many Data Mining-based methods that allow classifying of uncertain and incompletely specified data [37,39]. In this paper, the Fuzzy Decision Tree is used for the classification of initial data to construct the structure function. The advantage of this classifier is the possibility of visualisation of the process of decision making, which is very important for healthcare application [1,39].

In this paper, the proposed method for the construction of the mathematical representation of a system in the form of the structure function, based on uncertain and incompletely specified data, is used for evaluating COVID-19 patients' condition. The data about coronavirus disease is uncertain and incompletely specified at the presented time [10,22,37]. The initial data for some investigation of the problems correlated with COVID-19 were collected based on questionnaires [9] or expert knowledge [22]. The review in [22] shows the efficiency of methods based on Data Mining and Machine Learning techniques in COVID-19 diagnosing. However, in addition to diagnosing the disease, it is important to investigate, evaluate, and quantify, if it possible, the factors that have influenced a patient's

condition. An important investigation is the quantification of this influence. In this paper, the quantification of these factors is performed based on an importance analysis approach, which in reliability engineering is used to evaluate the influence of the system state change depending on the change of its component state [40,41]. Many algorithms in importance analysis are developed for the mathematical representation of the investigated system in the form of the structure function [1,32,40,41]. These algorithms can be used for quantification of the factors influencing the COVID-19 patient's condition without modification, which simplifies the evaluation.

The paper is structured as follows. The important aspects of the structure function definition and construction are presented in Section 2. The interpretation of this mathematical representation as a classifier is considered in this section too. This interpretation allows us to use methods from Data Mining for the construction of the structure function based on uncertain data. The principal steps of this method are introduced and explained in Section 3. The constructed structure function can be evaluated by the indices and measures from reliability engineering. Some of the most often used indices in quantification analysis of reliability are shown in Section 4. The application of the proposed method for the construction of the structure function based on uncertain data, and its evaluation by the chosen reliability indices and measures, are shown in Section 5. This example is based on a data set of COVID-19 patients. In this study, we consider the influence of the background information of the patients (sex and age), the accompanying illnesses (diabetes and obesity), and the impact of intubation on the patient's state.

## 2. Structure Function and Uncertain Data

### 2.1. System Mathematical Representation

The reliability analysis of any system starts by the mathematical representation of the investigated system/object based on initial data about the system structure and/or system behaviour from the point of view of reliability engineering [20,27,34]. The mathematical representation is constructed depending on (a) the number of system states (performance levels), and (b) the mathematical methods used for the system analysis and evaluation.

Two mathematical representations of the system in reliability analysis are used according to the number of system states: the Binary-State System (BSS) [26] and Multi-State System (MSS) [30,42]. BSS permits to identify two states in the system mathematical representation, which are failure and working or functioning of the system and its components. MSS permits to consider more states in the mathematical representation of the system. Of course, MSS is the more detailed mathematical representation of the system. However, MSS has not been widely used in reliability analysis due to two restrictions. The first restriction is computational complexity [42]. An additional system, and its components' states in the analysis, cause a dramatical increase in the mathematical representation's dimension. The second restriction is the lack of efficient methods for qualitative and quantitative MSS estimation [31,34,42]. So, the BSS is the dominantly used mathematical representation in reliability engineering.

The second factor that impacts the results of the mathematical representation of the system is the mathematical background used for the indices and measures calculation [42]. According to the analyses in [27,28,31,34], there are several principal groups of methods in reliability engineering: statistical methods, UGF-based methods, Monte-Carlo simulation methods, and methods used as a structure function. The methods for evaluation of a system based on the structure function have been developed. The important advantages of these methods are the simplicity of its construction and the possibility to represent the system of any structural complexity. The disadvantage of this mathematical representation is the impossibility of constructing the structure function based on incomplete or uncertain specified data [33]. A method for the structure function construction based on incompletely specified data is proposed in this paper.

### 2.2. Structure Function

The structure function of an  $n$  components system is defined as

$$\phi(x) = \phi(x_1, \dots, x_n):\{0,1\}^n \rightarrow \{0, \dots, 1\}, \tag{1}$$

where  $x_i$  is the  $i$ -th system component state, which can be  $x_i = 0$  if the component fails and  $x_i = 1$  if the component is functioning; the system states agree with the structure function value by the similar way,  $\phi(x) = 0$  if the system is faulty and  $\phi(x) = 1$  for the identification of the working system state.

The structure function (1) defines the dependence between all possible combinations of the system components states and the system state. The state vector  $x = (x_1, \dots, x_n)$  defines the states of the system components. Therefore, the structure function is defined for all possible state vectors. The structure function (1) is time independent and can be used for system evaluation in a stationary state or fixed time [26,31].

For example, consider a simplified laparoscopic surgery procedure from [43]. This system consists of four components ( $n = 4$ ): two doctors (an anaesthesiologist ( $x_1$ ) and a surgeon ( $x_2$ )), a nurse ( $x_3$ ), and a laparoscopic robotic surgery machine (technical component ( $x_4$ )). This system structure function according to (1) can be defined by the truth table (Table 1). In this table, symbol "f" denotes 0 (fault) and symbol "w" denotes 1 (work).

**Table 1.** Binary-State System (BSS) structure function of the system of a simplified laparoscopic surgery procedure [43].

$x_1$	f	f	f	f	f	f	f	f	w	w	w	w	w	w	w	w
$x_2$	f	f	f	f	w	w	w	w	f	f	f	f	w	w	w	w
$x_3$	f	f	w	w	f	w	w	w	f	f	w	w	f	f	w	w
$x_4$	f	w	f	w	f	w	f	w	f	w	f	w	f	w	f	w
$\phi(x)$	f	f	f	f	f	f	f	f	f	f	f	w	f	w	w	w

In Table 1, the system states are defined for all possible state vectors. There is another representation of the structure function in Table 1. All state vectors in the table can be divided into two groups. One group consists of state vectors for which the structure function value is 0. Another group joins the state vectors, which agree with the structure function value 1. This function can be presented by two classes (Table 2).

**Table 2.** Two classes of Binary-State System (BSS) representation.

$\phi(x)$	0	1
State vectors	0000, 0001, 0010, 0011, 0100, 0101, 0110, 0111, 1000, 1001, 1010, 1100	1011, 1101, 1110, 1111

This classification principle can be used for the structure function building based on incomplete or uncertain data, too. The structure function building must take into account two aspects. The first is the incomplete specification of system states, which needs finding, and determination of the unspecified system states. The second represents the ambiguity of the data values. Therefore, the structure function building can be interpreted as a classification task for incomplete or uncertain data. It is a typical task of Data Mining [37,44,45]. One of the approaches for solving this task is the application of a Fuzzy Decision Tree [14,44].

The uncertainty of the initial data for the structure function building also can be caused by the ambiguity of the initial data, and thus not only by the incomplete specification of all system states. This type of uncertainty can result from an expert’s subjective evaluation: some experts can indicate different values for an equal situation [46,47]. For example, two experts indicate a system failure for the situation where an anaesthesiologist’s work is not acceptable, but a third expert does not consider this situation as critical for system operation. The ambiguity of the data can be taken into account by the interpretation of the

components states and system states as fuzzy values [48]. The considered assumptions for the initial data uncertainty resulted in its interpretation as fuzzy incompletely specified data. The structure function construction was implemented based on a fuzzy classifier in this case.

For example, the structure function of a laparoscopic surgery procedure (Table 1) was constructed based on uncertain data by the considered method. The initial data were defined for the 12 combinations of the component states (Table 3). These data were collected and formed as expert evaluation of the laparoscopic surgery procedure. Therefore, every system component state and system states were defined with some possibility (confidence). Every component state and system state in Table 3 has a value 1 and 0, with the indicated confidence, which has a value from 0 to 1. These confidences, according to previous studies [33,49], are interpreted as a fuzzy membership function. For example, consider the value of the structure function  $\phi(x)$  in the first row. The structure function has a value a 0 with a confidence 0.7 and can be equal to 1 with a confidence of 0.3. This uncertainty can be taken into account by the interpretation of these values as fuzzy values.

**Table 3.** Uncertain data of a laparoscopic surgery procedure.

$x_1$		$x_2$		$x_3$		$x_4$		$\phi(x)$	
0	1	0	1	0	1	0	1	0	1
0.5	0.5	0.9	0.1	0.7	0.3	0.7	0.3	0.7	0.3
0.8	0.2	0.8	0.2	0.8	0.2	0.1	0.9	0.8	0.2
0.8	0.2	0.8	0.2	0.3	0.7	0.2	0.8	0.9	0.1
0.9	0.1	0.2	0.8	0.8	0.2	0.9	0.1	0.8	0.2
0.8	0.2	0.1	0.9	0.0	1.0	0.0	1.0	0.8	0.2
0.1	0.9	0.9	0.1	0.4	0.6	0.8	0.2	0.9	0.1
0.0	1.0	0.8	0.2	0.8	0.2	0.0	1.0	0.7	0.3
0.1	0.9	0.9	0.1	0.2	0.8	0.3	0.7	0.2	0.8
0.1	0.9	0.1	0.9	1.0	0.0	0.5	0.5	0.9	0.1
0.1	0.9	0.0	1.0	1.0	0.0	0.0	1.0	0.1	0.9
0.2	0.8	0.2	0.8	0.1	0.9	0.9	0.1	0.1	0.9
0.1	0.9	0.1	0.9	0.1	0.9	0.4	0.6	0.2	0.8

The structure function construction based on incomplete or uncertain data is not a typical problem in reliability engineering. Therefore, a special method for the structure function building should be developed.

### 2.3. Related Studies

In this paper, a new method for the structure function construction based on uncertain and incomplete data is considered. This method was developed based on knowledge of reliability engineering [26,27,42] and Data Mining [37,44,45]. The proposed method, from a point of view of reliability analysis, was elaborated taking into account the problem of the system mathematical model representation based on uncertain data. The problem of uncertain data is often considered in reliability analysis. It is statistical uncertainty in most of studies [28,34,50]. However, in the case of the data in the healthcare domain, the cognitive uncertainty should be taken into account, too [26,33,43]. This uncertainty is the result of ambiguity of the collected data in healthcare, which often is defined by expert evaluation [46,47]. This type of uncertainty can be taken into account in a system evaluation by the interpretation of the initial data as fuzzy data [48,49]. In our previous investigation [33], the theoretical background of the use of fuzzy data in the structure function was considered. The authors in [48,49] have shown the possibility of the fuzzy data application for the system evaluation, if the initial mathematical representation has been constructed. In [49], it is a fault tree, which is one of forms of the structure function. The structure function (1) as the mathematical representation of the system in the form of a fault tree indicated all the possible system states that lead to system failure [33]. Therefore, the structure function can be interpreted as a classification structure. In this case,

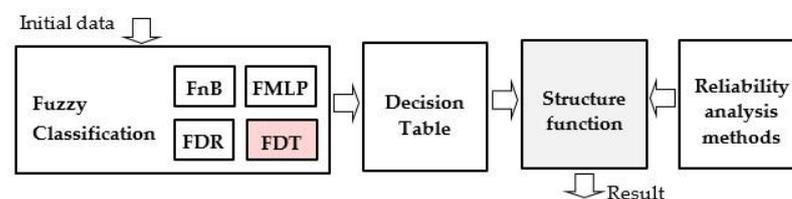
the problem of the structure function construction based on uncertain and incompletely specified data can be transformed into a problem of the classification of uncertain and incompletely specified data. In [33], the accuracy of FDT use for the structure function was evaluated. This evaluation has shown that the FDT can be effective for the structure function construction. In this paper, we continue this investigation and propose the calculation of some of the indices and measures for the system evaluation, in particular, the importance indices [32,40,41]. These indices allow quantifying the influence of the system component state change (component fault) to the system change (failure).

The construction of the mathematical representation (structure function) of the system based on uncertain and incompletely specified data is relevant for system analysis in healthcare. One of the classes of problems based on such data analysis is HRA in healthcare [1,16,51,52]. Another class is evaluation of the healthcare system under conception of a socio-technical system [21,23]. This class includes the problem of the disease diagnosis and the results of the diagnosis evaluation [7,14]. In this paper, we propose the decision of this problem based on the proposed method for the system structure function construction and the system evaluation based on the method of importance analysis. This decision is illustrated based on data for COVID-19 patients: the influence of patient sex and age, accompanying illnesses (diabetes and obesity), and intubation on his/her condition.

### 3. Method of the Structure Function Building

The incomplete or uncertain data analysis was implemented based on methods of Knowledge Discovery in Database or Data Mining as a rule. The interpretation of the structure function construction as the classification allows us to use the method of Knowledge Discovery in Database to induct a classifier, which divides the known and new (which was not defined in initial data) system states into groups of faulting and working. In other words, the inducted classifier permits to construct a decision table that includes all possible state vectors for the system component states and the corresponding system state for each state vector. The formed decision table is the structure function (1), according to its definition. This structure function can be analysed by well-known methods in reliability engineering to evaluate the risk or reliability of the systems. Because the initial data can be fuzzy, according to initial assumption, the method for the structure function building and its evaluation consists of the following principal steps (Figure 2):

- The induction of a fuzzy classifier based on the initial data.
- The building of the decision table based on the inducted classifier.
- The interpretation of the decision table as the structure function and the computation of the indices and measures for the reliability and risk evaluation.



**Figure 2.** The structure of the methods of the risk and reliability analysis based on incomplete or uncertain initial data.

The first step of the fuzzy classifier induction can be implemented based on the different approaches [44]. This can be implemented by fuzzy classifiers such as Fuzzy Naïve Bayes (FnB), Fuzzy Decision Rules (FDR), Fuzzy Multi-Layer Perceptron (FMLP), or Fuzzy Decision Tree (FDT).

In this paper, FDT is considered as a classifier for the structure function construction [33]. FDT is one of the types of decision trees. According to a review [22], the decision tree is the most often used classifier, used in COVID-19 detection and diagnosis. The FDT allows to operate with incomplete or uncertain data and fuzzy logic methods. Deci-

sion trees are among the most popular classifier given their intelligibility and simplicity. The building of the decision table based on FDT is very simple: all possible values of input attributes are defined for the classification samples and the result of the classification is corresponded to the class attribute. The structure function based on the decision table is formed through the interpretation of the values of the input attributes, as the values of the structure function variables (components states), and the class attribute values, as the structure function value (system state). The evaluation of the structure function is possible by the measures and indices of the reliability analysis.

The initial data for building the decision tree or FDT are the values of  $n$  independent input attributes/parameters  $A_1, \dots, A_n$  and their corresponding values of the target attribute/decision  $B$ . The value of the target attribute depends on the state of the independent input attributes. The values of the input or target attributes can be obtained as result of quantitative measures and/or qualitative expert evaluation of the real objects or processes.

FDT is a tree structure that consist of nodes, branches, and leaves. The node of a decision tree is associated with a state of input attribute. In accordance with the state of attributes in a node, the tree splits into branches/edges. The number of branches per each node corresponds to the number of possible states of this attribute. The end of the branch that does not split anymore is a leaf. The leaf corresponds to the decision/values of the target attribute. Decision making per instance is the path from the tree's root to the leaves through several branches. Selection of these branches depends on the state of the nodes (values of input attributes) per each instance in this path.

Decision tree and FDT are powerful tools used for visualisation and explicit description of the decision-making process in decision analysis.

The following are the advantages of the FDT classifiers: (a) simple to understand and interpret; (b) different possible scenarios of decision making can be analysed by this tool; (c) easy transformation to a decision table and collection of if-then decision rules; and (d) simple implementation into decision-making support systems and expert systems.

The use of FDT for the structure function construction aids the definition of the correlation of terminologies of the reliability engineering and classifier induction. The system state is interpreted as the class attribute and the component states are considered as the input attributes: the component  $x_i$  corresponds to the input attribute  $A_i$ . Each attribute  $A_i$  ( $1 \leq i \leq n$ ) is measured by two values of the attribute that correspond to the values of the  $i$ -th component states:  $\{A_{i,0}, A_{i,1}\}$ . The class attribute (the system state defined by the structure function value  $\phi(x)$ )  $B$  has two values,  $B_0$  and  $B_1$ .

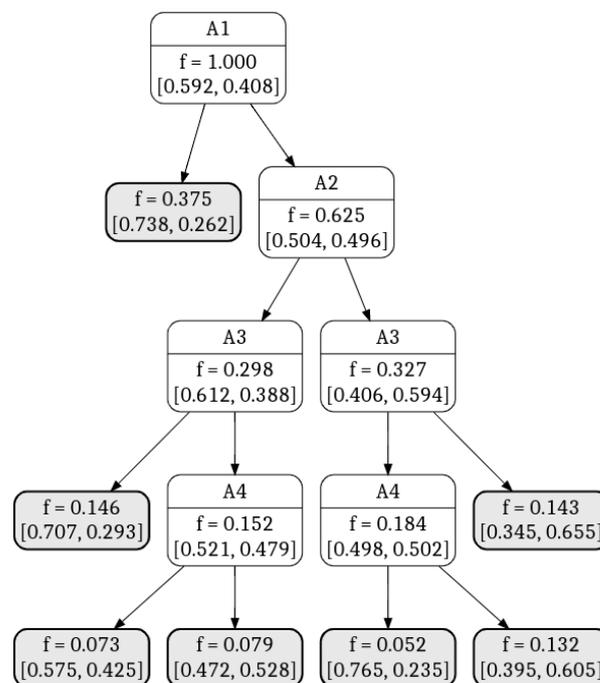
For example, the initial data of the laparoscopic surgery procedure consist of input attributes  $\{A_1, A_2, A_3, A_4\}$  and class attribute  $B$ . In this case, the attributes  $\{A_1, A_2, A_3, A_4\}$  correspond to the components  $x_1, x_2, x_3, x_4$ . The values of these attributes are values of the component states, which are in Table 3. The class attribute  $B$  agrees with the system states and its values are values of the structure function in Table 3. All values of the input attributes and class attribute are interpreted as fuzzy values for the induction of the classifier.

The fuzzy classifier for the structure function construction can be inducted according to the different approaches. In this paper, we propose to use FDT. FDT can be inducted based on cumulative information estimates, which is considered in detail in [33]. The concept of this method is based on the selection of the input attribute with maximal influence on the result and its association with the non-terminal node. The influence is evaluated by the cumulative information estimations. Two parameters are calculated and associated with every node: frequency  $f$  of this node and the confidences of values of the class attribute for this node. Two thresholds  $\alpha$  and  $\beta$  are introduced for FDT induction. The values of  $\alpha$  and  $\beta$  can be defined from 0 to 1. A tree's branch is stopped by the leaf if (a) its frequency  $f$  is less than the indicated value of  $\alpha$  or the confidence of one of the values of class attribute is greater than  $\beta$ . The  $\alpha$  and  $\beta$  values in FDT induction are the key parameters needed to transform the node into a leaf. Decreasing the threshold  $\alpha$  and increasing the threshold

$\beta$  allows us to build large FDTs. Large FDTs describe datasets in more detail. However, these FDTs are more sensitive to noise in the data. The values of thresholds  $\alpha$  and  $\beta$  are selected empirically and evaluated at the training step of the FDT induction. The initial data are divided for the training and controlled sets. FDT is inducted based on the training set for the fixed values of  $\alpha$  and  $\beta$ . The controlled set allows the evaluating accuracy and sensitivity of the inducted FDT. If the accuracy and sensitivity are not sufficient, another FDT is inducted for other values of the thresholds  $\alpha$  and  $\beta$ .

For example, for the simplified laparoscopic surgery procedure, the values of these thresholds were selected as  $\alpha = 0.15$  and  $\beta = 0.70$ . The FDT inducted based on the dataset in Table 2, according to these thresholds, is shown in Figure 3. The FDT in Figure 3 has non-terminal nodes that are indicated by the associated attributes. The second row in the non-terminal node is frequency  $f$  (it is more than indicated  $\alpha$  for non-terminal node). The two numbers of the last row are the confidence of values 0 (left number) and confidence of value 1 (right number) of the associated attribute. These values should be less than the threshold  $\beta$  for non-terminal nodes. Let us illustrate the context of the non-terminal node associated with attribute  $A_2$ . The frequency that this attribute will be analysed with after upper attribute(s) consideration is  $f = 0.625$  ( $\alpha = 0.15$ ). The confidence of the value 0 of this attribute is 0.504 and the confidence of the value 1 is 0.496 ( $\beta = 0.70$ ). The leaves of this FDT are indicated by the frequency  $f$  and the confidences of the values of the class attribute (the left number is confidence of the value 0 and the right number is confidence of the value 1).

The decision table of this classifier is presented in Table 4. The forming of the decision table is implemented by the classification of all possible values of the input attributes  $A_1, A_2, A_3,$  and  $A_4$ . Note that the value  $A_{i,j}$  of each attribute  $A_i$  is 0 or 1, with a confidence of 1. For example, the sample  $\{A_{1,1}, A_{2,1}, A_{3,0}, A_{4,0}\}$  is defined by values  $A_{1,1}$  and  $A_{2,1}$ , as 1 and values  $A_{3,0}$  and  $A_{4,0}$  as 0. The calculated class attribute  $B$  equals 0 with the confidence 0.765, according to the FDT in Figure 3. The value of the class attribute  $B$  is defined for every sample (the confidences of the values of the class attributes are shown in Table 4).



**Figure 3.** Fuzzy Decision Tree (FDT) of the simplified laparoscopic surgery procedure inducted based on data in Table 2 ( $\alpha = 0.15$  and  $\beta = 0.70$ ).

**Table 4.** Structure function of the simplified laparoscopic surgery procedure.

A <sub>1</sub>	A <sub>2</sub>	A <sub>3</sub>	A <sub>4</sub>	B	Confidence of Class Attribute B
0	0	0	0	0	0.738
0	0	0	1	0	0.738
0	0	1	0	0	0.738
0	0	1	1	0	0.738
0	1	0	0	0	0.738
0	1	0	1	0	0.738
0	1	1	0	0	0.738
0	1	1	1	0	0.738
1	0	0	0	0	0.707
1	0	0	1	0	0.707
1	0	1	0	0	0.575
1	0	1	1	1	0.528
1	1	0	0	0	0.765
1	1	0	1	1	0.605
1	1	1	0	1	0.655
1	1	1	1	1	0.655

The transformation from the decision table into the structure function is by the interpretation of the values of the input attributes as the values of the structure function and the values of the class attribute as the value of the structure function. It is the change of attributes A<sub>1</sub>, A<sub>2</sub>, A<sub>3</sub>, A<sub>4</sub> by variables  $x_1, x_2, x_3, x_4$  and attribute B by  $\phi(x)$ . For the considered example, this transformation is the changing of Table 4 by Table 1.

Therefore, the proposed method allows constructing the structure function of the investigated system based on uncertain and incomplete data. The constructed structure function is a typical mathematical model used in reliability analysis and can be quantified by well-known measures and indices of reliability engineering.

#### 4. Usage the Structure Function for System Evaluation

The quantification of the system is an important step in risk analysis and system reliability. There are known indices and measures that allow a system evaluation based on its mathematical representation by the structure function. Let us consider the group of basic indices for the system reliability analysis based on this mathematical representation. For the definition of these indices, there is the following assumption: the system is considered in the stationary state and a time independent analysis can be implemented in this case. The two most important indices for the system evaluation are availability and unavailability.

One of the important measures is availability  $A$ , which is defined as system functioning probability [26]:

$$A = Pr\{\phi(x) = 1\}, \quad (2)$$

and the system unavailability  $U$  is the probability that the system will not work [26]:

$$U = Pr\{\phi(x) = 0\} = 1 - A. \quad (3)$$

The system availability and unavailability can be calculated if the probability of every system component failure ( $q_i$ ) and functioning ( $p_i$ ) is known:

$$q_i = Pr\{x_i = 0\}, \quad (4)$$

$$p_i = Pr\{x_i = 1\}. \quad (5)$$

For example, the structure function of the laparoscopic surgery procedure presented in Table 1. Let the probabilities of these system components be defined as  $q_1 = 0.10$  ( $p_1 = 0.90$ ),  $q_2 = 0.10$  ( $p_2 = 0.90$ ),  $q_3 = 0.15$  ( $p_3 = 0.85$ ), and  $q_4 = 0.05$  ( $p_4 = 0.95$ ). We have to compute the availability and unavailability of this system. This availability and unavailability are computed according to (2) and (3).

$$A = Pr\{\phi(x) = 1\} = p_1 \times q_2 \times p_3 \times p_4 + p_1 \times p_2 \times q_3 \times p_4 + p_1 \times p_2 \times p_3 \times q_4 + p_1 \times p_2 \times p_3 \times p_4 = 0.8766 \quad (6)$$

$$U = 1 - A = 0.1234 \quad (7)$$

The system availability and system unavailability are very important reliability indices, which allow evaluating of the system as a whole. Beside these indices in reliability engineering, there are a group of indices that permit analysing the system components' influence on the system availability/reliability. The indices of this group are named "importance measures". These indices show the influence of every system component on system failure or functioning [40]. One of the simpler importance measures is Structure Importance (SI). SI of the  $i$ -th system component is defined as the probability of the system failure caused by the failure of this component. SI accumulates the system topological properties. This index is calculated based on the proportion of the system states that change their states depending on the  $i$ -th component's change in the space of all possible system states [40]. This index is computed based on the structure function as [40,41]:

$$SI_i = N_i / 2^{n-1} \quad (8)$$

where  $N_i$  is number of the system state (state vectors) for which the change of the  $i$ -th system component state result in the change of the system state.

According to study in [41], the number of the system states  $N_i$  in (8) can be defined based on Logical Differential Calculus (in particular, Direct Partial Logical Derivatives, DPLD). In Boolean algebra, the DPLD of the logical function allows indicating the function values for which the change of the  $i$ -th variable value from  $s$  to  $\bar{s}$  results in the change of the function value from  $j$  to  $\bar{j}$ . The definition of the DPLD agree with the conception of the importance measures, in particular, SI (8). In reliability analysis, DPLD is used for evaluating of the influence of the component fault to the system failure. Therefore, the DPLD of the structure function value changing from 1 to 0 with the respect of the variable  $x_i$  changing from 1 to 0 is considered in system reliability analysis [41]:

$$\partial\phi/\partial x_i = \begin{cases} 1, & \text{if } \phi(1_i, \mathbf{x}) = 1 \text{ and } \phi(0_i, \mathbf{x}) = 0 \\ 0, & \text{in other case} \end{cases} \quad (9)$$

or

$$\partial\phi/\partial x_i = \phi(1_i, \mathbf{x}) \wedge \overline{\phi(0_i, \mathbf{x})}, \quad (10)$$

where  $\phi(1_i, \mathbf{x}) = \phi(x_1, \dots, x_{i-1}, 1, x_{i+1}, \dots, x_n)$  and  $\phi(0_i, \mathbf{x}) = \phi(x_1, \dots, x_{i-1}, 0, x_{i+1}, \dots, x_n)$ .

The non-zero values of the derivative (9) correspond to the state vectors that indicate the component states influencing system failure if the  $i$ -th component fails. The non-zero values of the derivative are the number  $N_i$  in the definition of SI (8).

For example, a laparoscopic surgery procedure with the structure function in Table 1 has four logical derivatives, which are shown in Table 5. The numbers of the non-zero values for every derivative and SI of every structure component are shown in this table.

The first component of the system in this illustrative example has maximal influence on the system, because the SI of the first component has the maximal value.

Therefore, the proposed method (Figure 2) for the structure function construction based on uncertain data allows to form the mathematical representation of the system and implement the initial system reliability evaluation by well-known methods in reliability analysis.

**Table 5.** Logical derivatives of the structure function.

$x_2x_3x_4$	$\partial\phi(\xi)/\partial\xi_1$	$x_1x_3x_4$	$\partial\phi(\xi)/\partial\xi_2$	$x_1x_2x_4$	$\partial\phi(\xi)/\partial\xi_3$	$x_1x_2x_3$	$\partial\phi(\xi)/\partial\xi_4$
0 0 0	0	0 0 0	0	0 0 0	0	0 0 0	0
0 0 1	0	0 0 1	0	0 0 1	0	0 0 1	0
0 1 0	0	0 1 0	0	0 1 0	0	0 1 0	0
0 1 1	1	0 1 1	0	0 1 1	0	0 1 1	0
1 0 0	0	1 0 0	0	1 0 0	0	1 0 0	0
1 0 1	1	1 0 1	1	1 0 1	1	1 0 1	1
1 1 0	1	1 1 0	1	1 1 0	1	1 1 0	1
1 1 1	1	1 1 1	0	1 1 1	0	1 1 1	0
$N_1 = 4$		$N_2 = 2$		$N_3 = 2$		$N_4 = 2$	
$SI_1 = 0.50$		$SI_2 = 0.25$		$SI_3 = 0.25$		$SI_4 = 0.25$	

**5. Results**

We proposed a method for structure function building. The efficiency of this method can be considered based on the evaluation of the data about COVID-19 patients. The data used in the analysis is real data released by the Mexican Government. Therefore, we assume that the analysis is valid for Mexico and North America. This assumption is made given the fact that the pandemic statistics and behaviour are very different in Asian countries compared to North American or European countries due to much lower mortality in Asia. This dataset contains 566,602 instances where each instance represents a COVID-positive case identified in Mexico. These data were originally described by 21 attributes but for demonstration of our approach we selected five of them. The data in our analysis consist of five input and one class attributes. These input attributes are sex, intubation, diabetes, obesity, and age. All input attributes except age are binary (Table 6). The attribute age is numerical. The class attribute died identifies if the patient died.

**Table 6.** Attributes in the experimental investigation.

Attribute	Description
Sex ( $x_1$ )	Identifies the sex of the patient (1—man and 0—female)
Intubation ( $x_2$ )	Identifies if the patient required intubation (1—yes, 0—not)
Diabetes ( $x_3$ )	Identifies if patient suffers from diabetes (1—yes, 0—not)
Obesity ( $x_4$ )	Identifies if patient suffers from obesity (1—yes, 0—not)
Age ( $x_5$ )	Identifies the age of the patient
Died ( $\phi(x)$ )	Identifies if patient died (1—not, 0—died)

We have built FDTs for different thresholds of  $\alpha$  and  $\beta$ . We have estimated a classification accuracy for these thresholds. We have analysed  $\alpha$  from 0.0 to 0.25 and  $\beta$  from 0.700 to 1.0. Then the FDT with the best accuracy was selected. If there are FDTs with the same accuracy, we preferred the FDT with the bigger value of  $\alpha$  and smaller value of  $\beta$ . We chose the following thresholds:  $\alpha = 0.222$  and  $\beta = 0.800$ . The dependency of the classification accuracy on the different values  $\alpha$  and  $\beta$  is shown in Table 7.

When the best thresholds were chosen, we compared the proposed method based on FDT with other classifiers. In this comparison, we used the following metrics to evaluate the classifiers: classification accuracy, specificity, sensitivity, precision, and F1 score [51]. The accuracy shows the ratio of correctly classified instances. The sensitivity shows the ability of a classifier to identify positives while the specificity shows this ability for negatives. The precision is the proportions of positive and negative results in the statistics and diagnostic tests that are true positive and true negative results. The F1 Score is the harmonic mean of the precision and sensitivity. In the comparison was included the following classifiers: FDT, Decision Tree (DT) [44], Naïve Bayes (NB) [44], k-Nearest Neighbours (kNN) [44], Fuzzy Classification Rules [52], Fuzzy Multi-layered Perceptron (Fuzzy MLP) [53], Support Vector Machine (SVM) [44], and Neural Network (NN) [44].

Three of these classifiers work with fuzzy data and four of them work with CRISP data. The comparison is shown in Table 8.

**Table 7.** Classification accuracy of the structure function building for different thresholds of  $\alpha$  and  $\beta$ .

$\beta \setminus \alpha$	0.000	0.028	0.056	0.083	0.111	0.139	0.167	0.194	0.222	0.250
0.700	0.925	0.925	0.923	0.928	0.928	0.928	0.928	0.929	0.929	0.929
0.733	0.931	0.931	0.930	0.932	0.933	0.933	0.934	0.934	0.935	0.934
0.767	0.944	0.944	0.945	0.945	0.945	0.946	0.947	0.947	0.947	0.935
0.800	0.949	0.949	0.950	0.950	0.950	0.951	0.951	0.954	0.954	0.940
0.833	0.949	0.949	0.950	0.950	0.950	0.950	0.951	0.951	0.954	0.940
0.867	0.948	0.948	0.949	0.949	0.949	0.949	0.950	0.951	0.949	0.935
0.900	0.947	0.947	0.949	0.949	0.949	0.949	0.950	0.951	0.949	0.934
0.933	0.947	0.947	0.949	0.949	0.949	0.949	0.950	0.951	0.949	0.933
0.967	0.947	0.947	0.949	0.949	0.949	0.949	0.950	0.951	0.949	0.932
1.000	0.947	0.947	0.949	0.949	0.949	0.949	0.950	0.951	0.949	0.932

**Table 8.** Comparison of the classification algorithms for evaluation of patients with COVID-19.

Metrics of Classification Result Evaluation	FDT	DT	NB	kNN	Fuzzy Classification Rules	Fuzzy MLP	SVM	Neural Network
Accuracy	0.954	0.931	0.920	0.891	0.949	0.940	0.926	0.949
Specificity	0.965	0.944	0.943	0.925	0.963	0.958	0.944	0.981
Sensitivity	0.842	0.807	0.702	0.579	0.807	0.772	0.754	0.643
Precision	0.716	0.605	0.571	0.452	0.697	0.657	0.589	0.783
F1 Score	0.774	0.692	0.630	0.508	0.748	0.710	0.662	0.706

As the comparison shows, the fuzzy-based approach can outperform traditional crisp classifiers. This can result from the initial data that are uncertain and the fuzzy-based classifiers are taking into account this uncertainty. The best accuracy was obtained for FDT. This can indicate that this method is effective for this task.

The goal of the study is analysing the influence of all input attributes on the output attribute, which means the evaluation of sex, intubation, diabetes, obesity, and age influence on patient death. This investigation can be implemented by the initial data interpretation of the system for the reliability analysis and evaluation of the constructed mathematical representation by SI, to indicate the “most important” components (attributes) of this system.

The initial data are uncertain; therefore, the mathematical representation (the structure function) can be formed by the proposed method, which is based on FDT. The FDT of these data is shown in Figure 4. This FDT is induced for thresholds  $\alpha = 0.15$  and  $\beta = 0.70$ . The notation of the FDT nodes is similar to the FDT in Figure 3.

The decision table for this FDT is formed by the calculation of the class attribute values for all possible combinations of input attribute values. The decision table was transformed into a truth table of the structure function by replacing the input attributes values by the values of the structure function variables (component states) and values of the class attribute by the values of the structure function (system states). Table 9 is the truth table of the formed structure function. The constructed structure function can be used for the evaluation of the influence of the indicated components (parameters) on the result. This analysis can be implemented based on the calculation of SI for every one of the system components (parameters).

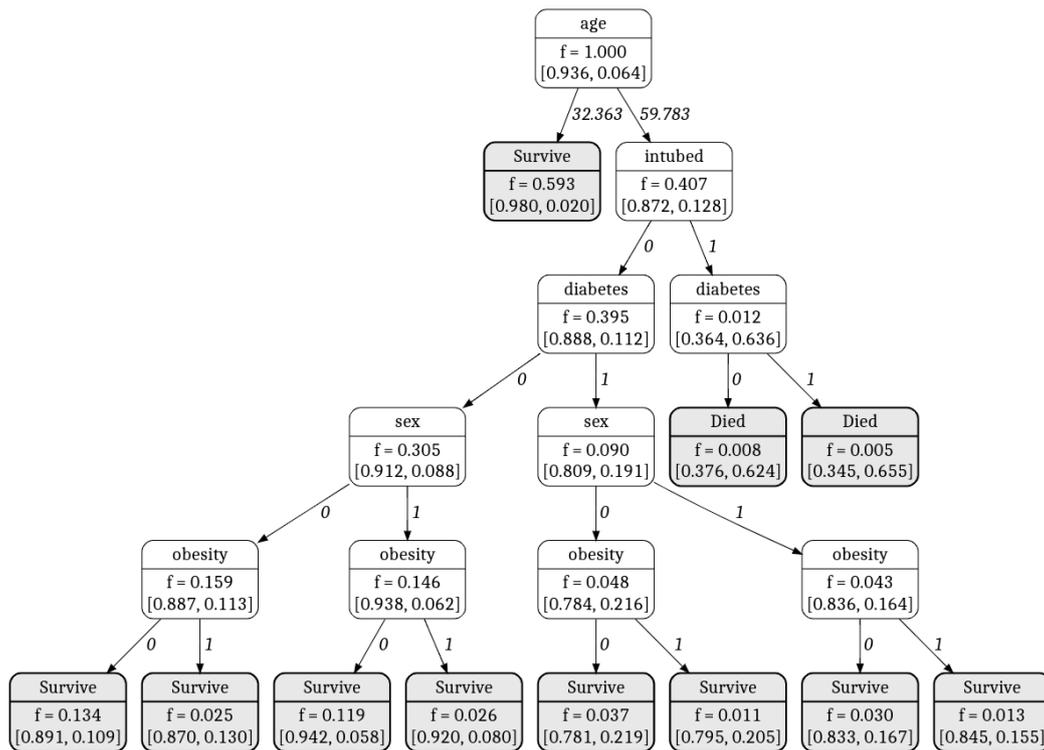


Figure 4. Fuzzy Decision Tree (FDT) for the investigated data.

Table 9. The structure function of the system for evaluation of COVID-19 patients.

		$x_4$	$x_5$	0	0	1	1
$x_1x_2x_3$		0	0	0	1	0	1
0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0
0	1	0	0	0	0	0	0
0	1	1	0	1	1	1	1
1	0	0	0	0	0	0	0
1	0	1	0	0	0	0	0
1	1	0	0	0	0	0	0
1	1	1	0	1	1	1	1

The SI for every parameter is computed according to (8) and  $N_i$  (number of critical states) is defined by the DPLD ((9) or (10)). The computed SI has a value of 0 for the first (sex), the fourth (obesity), and fifth (age) parameters:  $SI_1 = 0$ ,  $SI_4 = 0$ , and  $SI_5 = 0$ . The SIs for the second (intubation) and third (diabetes) parameters have a value of 1:  $SI_2 = 1$  and  $SI_3 = 1$ . Therefore, intubation and diabetes have the maximal influence on the state of the COVID patient. However, in a reliability engineering context, one needs to note that the value 1 of SI does not mean there is an unambiguous, non-variant influence of this parameter on the result. This value indicates the maximal possible influence between other parameters.

6. Discussion

A new method for mathematical representation construction based on uncertain data is proposed in this paper. The mathematical representation is constructed as the structure function of the system, which permits to use all known methods of the system analysis based on its representation in the form of a structure function. The novelty of the proposed method is the interpretation of the structure function as a classifier. It allows using a method for classifier induction (in our case FDT) for the structure function development.

Any classifier can be defined by the decision table. This table is considered as the truth table of the structure function. The analysis of the influence of the input attributes on the classification result is implemented by the importance analysis, in particular, based on SI (9a) or (b). The input attribute with the highest value of SI has the greatest impact on the result. This aspect of the application of the proposed method was used in an analysis of COVID-19 patients: we analysed and evaluated the influence of concomitant disease, age, and intubation.

The initial data for this analysis have been simplified. We did not use all the data presented in the investigated data (<https://www.gob.mx/salud/documentos/datos-abiertos-152127> (accessed on 28 October 2020), <https://www.kaggle.com/tanmoyx/covid19-patient-precondition-dataset?select=covid.csv> (accessed on 18 January 2021)). In this paper, only the technical aspects of the proposed method to analyse the influence of the input attributes on the classification result were considered. This study was performed without detailed consultation with doctors. Therefore, we do not publish results that could be interpreted as real recommendations. Similar studies based on real data were carried out and published in the work [54].

The evaluation of the proposed method accuracy, specificity, and other metrics (Table 8) shows that it has acceptable parameters and can be used for such evaluations. A comparison of some classifiers was implemented too. According to the result of this comparison, the FDT-based classifier for the considered problem has the best metrics.

One of the advantages of the proposed method is the different aspects and areas of its application. The application of this method should be considered as minimal according to two aspects. The first of them is its application in reliability engineering.

The possibility of the structure function building based on incomplete and uncertain data extends the applications of this mathematical representation. One of the possible application areas of this method can be the analysis of the human factor. Human Reliability Analysis (HRA) is one of the important parts of reliability engineering. The HRA methods permit to analyse failures in human communications and evaluate human failure and the impacted causes [51]. As a rule, the initial data in HRA is incomplete and uncertain. Therefore, the HRA method provides a qualitative analysis. Examples of such methods are the Human Error Assessment and Reduction Technique (HEART) [52] and Success Likelihood Index Method (SLIM) [53]. These methods analyse the frequency aspects of human error dominantly and predict the human error. Some of the HRA methods (for example, Cognitive Reliability and Error Analysis Method (CREAM) [54]) analyse the human cognitive aspects, the errors' causes rather than their frequency. However, the quantitative assessment in the HRA methods needs a reducing of the uncertainties of the initial data. Expert judgment is used extensively to compensate for a lack in data. However, the expert data have a specific uncertainty, too, which should be taken into account [55]. The proposed method for the building of the structure function based on incomplete data allows forming of the mathematical representation of the system with two factors of uncertainty, as incompletely specified and ambiguous, which is characteristic of expert data. The application of the proposed method in HRA can be efficient. It is illustrated by the manually calculated example presented in this paper.

Another possible application of the proposed method can be in healthcare safety [20,22]. One needs to note that the conception of health safety is correlated with the human factor evaluation [14–16]. There are special methods of human factor analysis in medicine, which have been developed based on typical methods of HRA: Observational Clinical Human Reliability Analysis (OCHRA) [55] and Healthcare Failure Mode Effect Analysis (HFMEA) [56]. Both of these methods are based on qualitative assessment of the human factor. The application of the proposed method allows quantitative assessment of the human factor in medicine.

The proposed method can be used not only to analyse the human factor, but also to construct the mathematical model in the form of the structure function (1) of any other model for which the initial data is not completely specified [34] or such data is heteroge-

neous [57]. Examples of such systems can be the evaluation of protection against terrorist attacks [58], critical infrastructure [59], drone fleet analysis [60], and other. The proposed method can be useful for structural reliability [61].

The next aspect of the proposed method application is analysis of the result of the classification, which can be used in problems of Data Mining. In future investigations, we plan to develop the proposed method based on the studies in Data Mining, too. In this paper, FDT was used as classifier for the induction of the structure function. This classifier is often explored in medical applications because it allows a good visualisation of the decision [22]; but, according to studies in [39,62,63], the Neural Network and Deep Learning methods are effective and have the best accuracy for many applications. The Deep Learning-based method has been used for COVID-19 detection based on X-ray image analysis [64], natural language processing [65], and epidemiology forecasting [66]. The Deep Learning and Neural Network methods can be effective for a reliability analysis. These and other classification methods in Data Mining have been well investigated [37,44,57,59,67]. There are many methods for the induction of different classifiers [14,44,67]. However, the problem of the analysis of the influence of the input attributes into the result of the classification has not been investigated sufficiently. The interpretation of the developed classifier as the structure function permits to quantify the influence of the input attribute to the output class of the decision. Such an investigation can be more effective if the structure function will be constructed for the MSS (it is introduced in Section 2.1). For example, the methods for the MSS analysis based on the existing structure function of MSS are presented in [32,42,68]. So, the proposed method can be used in applied problems of reliability engineering and data mining.

## 7. Conclusions

The construction of the mathematical representation (model) of the investigated system in a reliability engineering context is a very important step, because this mathematical representation aids the application of methods for the evaluation of system reliability by special indices and measures, and in some cases, a set of these indices and measures. Most of the often-used mathematical representations in reliability engineering need complete and precise data about the system's behavior. One of these mathematical representations is the structure function (1). The important advantages of the structure function as the mathematical representation in reliability engineering are the possibility to unambiguously represent the system of any structure complexity and numerous well-developed methods for the calculation of different measures. However, this mathematical representation cannot be formed based on incomplete and uncertain data.

A new method for building a structure function, as a mathematical representation of the system for reliability analysis, is presented in this paper. This method allows to build the structure function based on incomplete and uncertain data. The methodological background of the proposed method is the calculation of the structure function as the classification task and using the approach of classifier induction for the structure function building.

This method can be used for the evaluation of different types of systems in healthcare. In this paper, the method is used for the construction of the system, which allows for an analysis of the influence of some factors of disease on the condition of COVID-19 patients.

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