R.Graph: a New Risk-based Causal Reasoning and Its Application to COVID-19 Risk Analysis

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Abstract

Various unexpected, low-probability events can have short or long-term effects on organizations and the global economy. Hence there is a need for appropriate risk management practices within organizations to increase their readiness and resiliency, especially if an event may lead to a series of irreversible consequences. One of the main aspects of risk management is to analyze the levels of change and risk in critical variables which the organization's survival depends on. In these cases, an awareness of risks provides a practical plan for organizational managers to reduce/avoid them. Various risk analysis methods aim at analyzing the interactions of multiple risk factors within a specific problem. This paper develops a new method of variability and risk analysis, termed R.Graph, to examine the effects of a chain of possible risk factors on multiple variables. Additionally, different configurations of risk analysis are modeled, including acceptable risk, analysis of maximum and minimum risks, factor importance, and sensitivity analysis. This new method's effectiveness is evaluated via a practical analysis of the economic consequences of new Coronavirus in the electricity industry.

Keywords: R.Graph, Risk analysis, Causal chain, COVID-19

Abbreviations	
ANP	Analytic network process
AR	Acceptable risk
AXIOM	The advanced cross-impact option method
BM	Bayesian model
BN	Bayesian network
BASICS	Batelle scenario inputs to corporate strategies
CAST	Causal analysis based on systems theory
CIAM	Cross impact analysis model
COVID-19	Coronavirus disease of 2019
DBN	Dynamic Bayesian network
BWM	Best-worst method
DEMATEL	Decision-making trial and evaluation
EXIT	Express cross-impact technique
GDP	Gross domestic product
HAZOP	Hazard and operability study
HWA	Hybrid weighted averaging
INTERAX	The *acronym* for the futures research process
ISM	Interpretive structural modeling
MCM	Multi-criteria based model
MICMAC	Cross-impact matrix multiplication applied to classification
OECD	The organization for economic co-operation and development
OWA	Ordered weighted averaging
QFD	Quality function deployment
RBA	Risk-based approach
SARS	Severe acute respiratory syndrome
SMIC	Cross impact systems and matrices
SCC	Spearman's correlation coefficient
STAMP	Systems-theoretic accident model and processes
WAA	Weighted arithmetical averaging

1. Introduction

COVID-19 has rapidly led to unprecedented health, economic, and political crises across the globe [11], becoming a major risk factor for many organizations. Many companies have indicated that the impact of Coronavirus COVID-19 is, or will be, a significant source of uncertainty. According to the OECD Economic Outlook Interim Report (March 2020), annual global GDP growth projections for 2020 have dropped by half a percentage point to 2.4%, largely due to the coronavirus outbreak. However, a longer-lasting and more intense coronavirus outbreak could even slow global growth to 1.5% [26]. The coronavirus pandemic may eventually fade, as the Ebola, Zika, and SARS viruses have in recent history. However, even if it does, the next as-yet-unknown devastating outbreak is not so much a matter of "if" but "when." How, then, should organizations, societies and governments prepare for similar future possibilities? Even with the knowledge that such events may occur, there is a significant difference between mere awareness and the actual experience; evaluating the correct response to these potential future situations is vital for any company, institution, or country which wishes to remain competitive in the current globalized world [13].

One solution to increase resiliency is risk-informed development. Risk can be defined as the probability of a certain deviation in achieving a goal, which can be determined by modeling the interacting risk factors [38, 37]. Risk factors can be considered as effective factors which may cause variations in predictions [39]. Risk analysis constitutes a family of approaches to aid top managers in assessing all potential impacts through considering the criticality of various risk factors within systemic procedures.

Two significant aspects of specific risk are the probability of a risk occurring (known as stochastic uncertainty) and the variability and changes in predictive consequences (aleatoric uncertainty) [16]. Therefore, the risk of interactive risk factors on each other can be assumed in three different ways: 1) the effect of a specific risk factor on the probability of an event; 2) the effect of the risk factor on the severity of an event; and 3) the combined effect of the risk factor on the probability and severity of a consequence. For instance, let us assume the probability of a person being imprisoned for a certain period of time. For this, finding a new document in court or a further witness, as a factor, can have an effect on reducing or increase in the length of imprisonment, an increase/decrease in the probability of incarceration, as well as the simultaneous effect on the probability and duration of confinement.

One of the most effective methods for modeling and determining the probability and variability in a system is to break it down into smaller components through causality analysis models. These components can then be used to identify a set of factors that affect each other, examining a chain of causes and effects to make better predictions of risk and variability. The motivation for conducting this study is based on the fact that, in some risk analysis problems, the decision-maker is interested in knowing various change rates. These can relate to the occurrence of events that: have not been previously predicted; have already occurred; or have not yet occurred but may alter relevant predictions and variables. In many cases, either events happen or it is obvious to the decision-maker that the event will happen eventually. In such cases, the models can be assumed to be definite [16], thus only variability needs to be considered. Since, in the real world, many variables are continuous, it is necessary to develop a suitable model that can find the percentage of change predicted in the desired variables. The challenge for some of these issues is that the probability of certain events occurring may be very low, meaning that there is little data available for risk analysis. In these cases, therefore, instead of empirical or statistical data, the knowledge of experts in related fields can be employed during the process of evaluating the relationships between the model components [28].

There are several causal methods in the literature for risk analysis, whose various characteristics and disadvantages are investigated in Section 2. The motivation of this study is then to overcome these disadvantages and to find an appropriate solution; a causal mathematical model is proposed, called R.Graph. This model has the ability to estimate variability and risk while considering different scenarios in a causal chain of various factors. It uses data gathered from experts, while its outputs are easily interpretable and explicable by decision-makers.

The current paper is arranged in the following order. Section 2 surveys existing literature on causality models and methods of risk analysis, while Section 3 discusses the preliminaries of risk and aggregation operators. Section 4 sets out the R.Graph model. A relevant case study is presented in Section 5, and Section 6 summarizes the findings, and proposes insights for future research.

2. Literature review

In this section, the literature survey on causality models and their applications in risk analysis is provided in Section 2.1; the limitations of these methods, and the novel contributions of this paper are then presented in Section 2.2.

2.1. Literature survey on causality models and applications in risk analysis

There are various methods in the existing literature to analyze these causal chains, which can be divided into two categories: deterministic models including structural models [5], multi-criteria based models (MCBMs) [46] and probabilistic models, such as cross-impact analysis models (CIAMs) [28, 29], Bayesian models (BMs) [9], risk-based approaches (RBAs) [3], which are displayed in Fig. 1. In these approaches, the impacts of various scenarios are measured in different ways. For instance, CIAMs, BAs, and RBAs use probabilistic inference to deal with a variety of interactive risk analyses based on probabilistic input data. They can be used to examine the effects of event probability changes, and then identify requisite actions and interventions to reduce adverse effects [27]. In MCBMs and cognitive maps [25], the cause and effect between various interactive concepts are modeled.

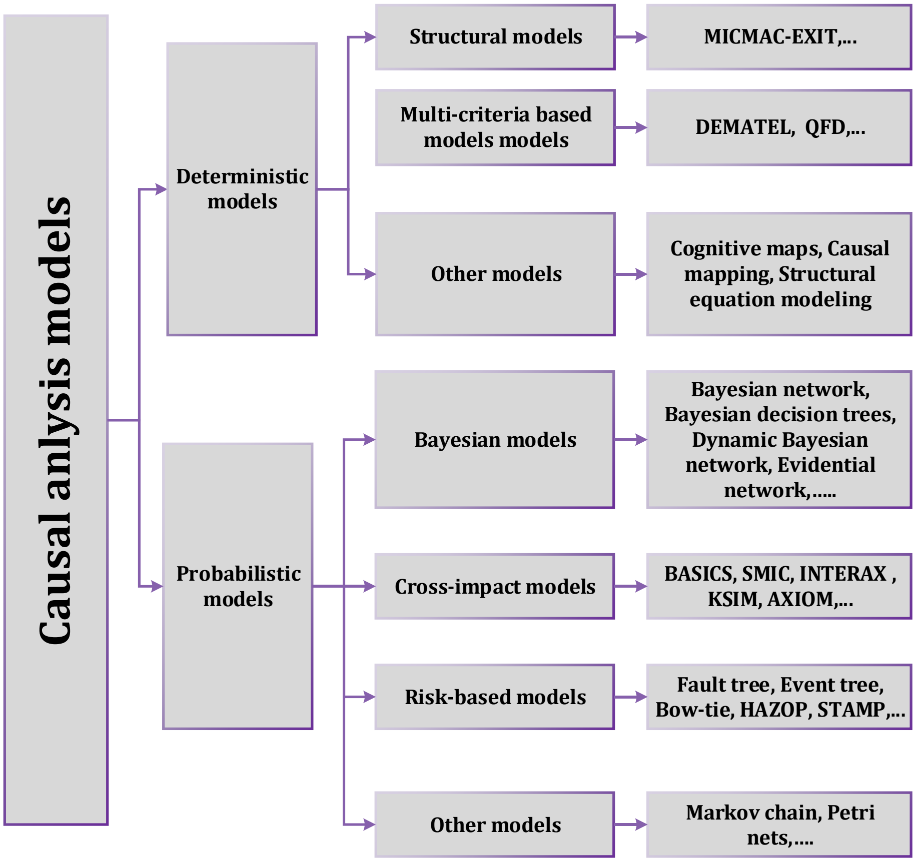


Fig. 1. Different causal analysis models

Various studies have been conducted to analyze the different aspects of risk analysis in distinct organizations, including Li et al. [22], who proposed a causal analysis based on the STAMP model for a safety risk analysis of underground gas pipelines. In this study, CAST analysis was adapted to examine safety flaws, revealing the series of reasons behind decisions made leading up to a catastrophic gas explosion. Yazdi et al. [43] augmented a new integrated approach – based on DEMATEL, BWM, and Bayesian network approaches – to assess the dependency between risk factors and information sources. BWM was employed to compute relative expert opinion weights, then DEMATEL was mapped into the BN in order to identify critical factors in a dynamic structure. The proposed method was utilized in high-tech safety management. In another study, Yazdi et al. [44] introduced an improved solution, termed Pythagorean fuzzy DEMATEL, to evaluate the interrelation of corrective actions within a probabilistic safety analysis of an offshore platform facility. Pythagorean fuzzy numbers were applied to conjoin expert judgment and the DEMATEL method to encompass randomness and uncertainty. Li and Wang [23] developed a fuzzy risk assessment methodology by integrating a fuzzy ANP and interpretive structural modeling, which captured interrelationships and interdependencies between risk factors and risk priorities to avoid data inaccuracy. ISM was used to identify critical risk factors, while fuzzy ANP was utilized to capture the fuzziness of neutral, optimistic, and pessimistic expert opinions, before ranking risk factors. This proposed method was implemented in construction and engineering risk management. A new risk analysis approach was proposed by Huang and Zhang [18] combining FMEA and pessimistic-optimistic FAD, while accounting for an acceptable risk coefficient. The method was employed in evaluating dangerous goods transportation system risk on a railway. Tran et al. [42] published a hybrid CIAM and factor analysis model for modeling cost variances in highway project-delivery decisions. Chen et al. [8] proposed a model for the risk analysis of a multi-reservoir system, employing Monte Carlo simulations, dynamic Bayesian networks, and risk-informed inference. In this paper, Monte Carlo simulations were utilized to provide inputs for DBN, then DBN was built through expert knowledge uncertainty interrelationships. Finally, risk-informed inference provided risk information by a trained DBN. Drakaki et al. [12] proposed a risk-informed supplier selection based on integrating fuzzy cognitive maps and a risk-based FAD (RFAD). Here, FCM was used to capture between-criteria dependencies, while RFAD was used to rank suppliers. Li et al. [21] proposed a three-stage approach integrating DEMATEL, ISM, and BN. As a first step, a hierarchical network model was presented combining DEMATEL and ISM methods, thus investigating the coupling relationships between various accident-related factors and BN structure. The hierarchical structure was mapped onto a BN in order to quantify the strength of relationships between accident leading systems, specifying the main resultant systemic cause.

2.2. Limitations of existing methods and novel study contributions

Each available causality analysis method (Fig.1) has certain drawbacks in terms of analyzing the main research problem. For example, existing risk analysis methods, such as fault tree [19] and event tree [32], only determine the probability of risk occurrence or the probability of occurrence of the desired outcome. They are thus unable to determine the rate of change and the new values of variables due to risk factors. In CIAMs, the effect of a risk factor is modeled only on probability. When the goal is to investigate the impact of a risk factor on the severity and probability of an event, this can be achieved by defining discretely different scenarios (states) and assigning probabilities to each of them. However, increasing states requires a large number of evaluations, causing the complexity of the problem to grow exponentially [29]. Moreover, due to a consideration of discrete values, it does not provide a good estimate of the continuous values provided to decision-makers. Bayesian methods can be divided into two categories: discrete and continuous. Discrete methods have the same drawbacks as the CIAM [31], while continuous methods first require sufficient data to estimate the probability function. This is often unavailable in the problem, and is used less frequently by decision-makers due to its computational complexity. In definite methods such as MCDM, structural models, and cognitive maps, only the degree of importance and effectiveness of a risk factor is considered among all factors, not the percentage of variability. For these reasons, they are more useful for ranking risk factors rather than for risk prediction, and thus are not suitable for use in the problem mentioned. Finally, the limitations of certain traditional data-driven methods like structural equation modeling [2] include a lack of access to data, due to quantification problems within the essential systemic parts. Moreover, decision-makers are often reluctant to rely on data-based models unless it is immediately clear what the results will [4]. If this clarity is lacking, it provides a major concern for management, since they wish to take appropriate decisions with confidence, comprehension, and clarity.

According to the above, the purpose of this paper is to develop a new method of causes and effects which considers the impacts of different factors on each other in a network structure. The aims are to be able to: 1) estimate a risk degree of a factor according to other inputs, instead of considering an overly extensive number of discrete scenarios; 2) use the data obtained from experts to perform risk analysis in cases where data is not available; 3) consider different configurations of risk analysis (such as acceptable risk, maximum and minimum risks, factor ranking and sensitivity analysis); and finally, 4) be analyzable, interpretable, and explicable for decision-makers. The resulting new method is termed *R.Graph* within this paper. To test the effectiveness of this new model, a case study is presented in order to investigate the effects of COVID-19 on financial parameters of Iranian electricity industry.

3. Preliminaries

In this section, the required prerequisites for developing the proposed R.Graph model are presented. These include the definitions of relative difference and risk, as well as the operators of the aggregation process, in Sections 3.1 and 3.2, respectively.

3.1. Relative risk

Absolute difference refers to the difference between a compared value and a specified reference value. Considering two variables, y and x, however, allows the absolute difference to be described in comparison with a reference value [41]. The relative difference between x and y can be measured, then defined as a real-value function $R(x, y)$ [41]. This function involves positive arguments x and y, $R: \rightarrow \mathbb{R}$, and possesses the following properties [41]:

(a) $R(x, y) = 0$, if $x = y$.

(b) $R(x, y) > 0$, if $y > x$.

(c) $R(x, y) < 0$, if $y < x$.

(d) R is a continuous, increasing function of y when x is fixed.

(e) $\forall \lambda: \lambda > 0 \rightarrow R(\lambda x, \lambda y) = R(x, y)$.

The risk or error of definite data can be defined as the deviation of the exact parameter from the predicted value using relative change measure, which can be determined as follows [40]:

$$R = \frac{|Predicted\ value - Exact\ value|}{Exact\ value} \tag{1}$$

Therefore, the risk of E_2 in accordance with E_1 can be defined by employing Eq. (1) [40]:

$$R = \frac{|E_2 - E_1|}{E_1} \qquad r \geq 0 \tag{2}$$

in which we have:

$$\begin{cases} E_2 = (1+R)E_1 & if E_2 \geq E_1 \\ E_2 = (1-R)E_1 & if E_2 < E_1 \end{cases} \tag{3}$$

3.2. Aggregation operators

In this section, several fundamental definitions are introduced with regard to aggregation operators used in the R.Graph methodology.

Definition 1 [24]. The weighted arithmetical averaging (WAA) operator with dimension n is a mapping WAA: $\mathbb{R}^n \rightarrow \mathbb{R}$. This is defined by the following formula:

$$WAA(a_1, a_2, \dots, a_n) = \sum_{i=1}^{n} w_i a_i \tag{4}$$

where $W = (w_1, w_2, \dots, w_n)^T$ is the weighting vector of real numbers $a_1, a_2, \dots, a_n$, such that $\sum_{i=1}^{n} w_i = 1$ and $w_i \in [0,1]$, $\mathbb{R}$ is the set of the real numbers.

Definition 2 [24]. The ordered weighted average (OWA) aggregation operator of dimension n is a mapping: $\mathbb{R}^n \rightarrow \mathbb{R}$. It possesses the weighting vector $\acute{W}$ as follows:

$$\acute{W} = (\acute{w}_1, \acute{w}_2, \dots, \acute{w}_n)^T \tag{5}$$

where the component $\acute{w}_\mathrm{I}$ $(i = 1,2,\dots,n)$ of weighting vector $\acute{W}$ is subject to the following constraints: $\acute{w}_\mathrm{I} \in [0,1]$ and $\sum_i \acute{w}_\mathrm{I} = 1$.

Following on from this, an OWA operator can be expressed as:

$$OWA(a_1, \dots, a_n) = \sum_{i=1}^{n} \acute{w}_\imath d_i \tag{6}$$

with d_i being the i-th largest of the a_i $(1,2,\dots,n)$.

Using the various advantages of operators WAA and OWA, a hybrid weighted averaging (HWA) operator may thus be defined:

Definition 3 [24]. The HWA operator of dimension n is a mapping: $\mathbb{R}^n \rightarrow \mathbb{R}$. It is defined by an associated weighting vector $\acute{W} = (\acute{w}_1,\ \acute{w}_2, \dots,\ \acute{w}_n)^T$, such that $\sum_{i=1}^{n} w_i = 1$ and $w_i \in [0,1]$, and may be expressed as the following formula:

$$HWA(a_1, a_2, \dots, a_n) = \sum_{i=1}^{n} \acute{w}_\imath d_i \tag{7}$$

where d_i is the i-th largest of weighted arguments $nw_i a_i (i = 1,2, \ldots, n)$, and $W = (w_1, w_2, \ldots, w_n)^T$ is the weighting vector of $a_i (i = 1,2, \ldots, n)$, with $\sum_{i=1}^{n} w_i = 1$ and $w_i \in [0,1]$. n here is a balancing coefficient.

4. Risk analysis using R.Graph methodology

In this section, the proposed R.Graph method is developed, and its various configurations are investigated (Section 4.1). In addition, a new group risk analysis framework based on the proposed R.Graph is presented (Section 4.2).

4.1. R.Graph methodology

The purpose of this section is to examine the different risk scenarios and changes in the causal chain, utilizing expert knowledge and presenting the concepts of the R.Graph model. Therefore, the main definitions and ideas of the R.Graph methodology are discussed in Section 4.1.1. Consistency checking; acceptable risk; determining pessimistic and optimistic risk values; identifying critical factors; and sensitivity analysis are laid out in Sections 4.1.2, 4.1.3, 4.1.4, 4.1.5, and 4.1.6, respectively.

4.1.1. R.Graph definitions and concepts

Considering a chain of acyclic causes and effects influencing each other, the goal of the R.Graph method is to investigate the percentage change in each factor due to changes in other factors, or the occurrence of different events over a fixed period of time. In this case, assuming the model is definite, the following concepts are first defined:

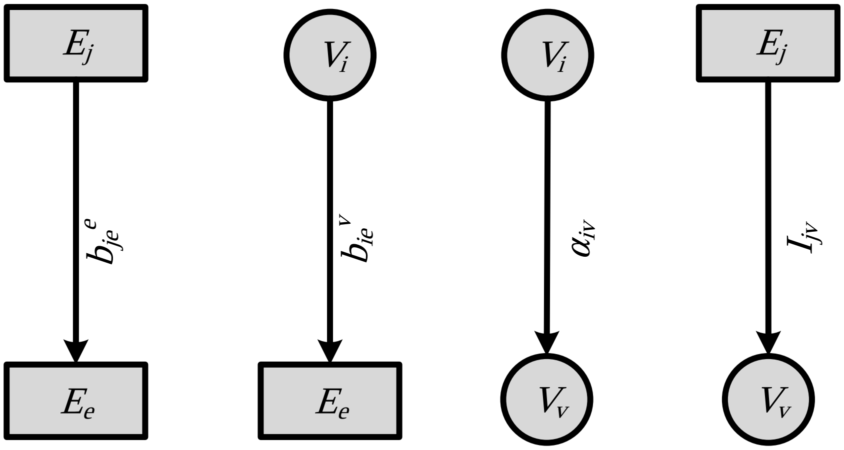
Variable: The variable in this study is set as any factor that has the ability to accept a value and a quantity as intensity, and all variables are considered to be continuous and definite. If there is a causal relationship between the two variables, a change in the cause variable can lead to a change in the effect variable. Generally, mathematical functions can be defined for variables. For instance, cost, time, and speed can be examples of a variable. In the proposed R.Graph method, the ith variable is shown as V_i and in the form of a circle.

Event: Event is a factor without intensity and quantity, or is the variable whose change in value is not examined; it is generally stated by zero and one values. The occurrence of one event can cause the presence of other events, or change the value of other variables. For instance, the existence of natural disasters, such as floods and earthquakes, can be considered an event. In the proposed R.Graph, an event j is shown as E_j and in the form of a rectangle.

Factor: Each variable or event is called a factor.

Parent: If there is a cause and effect relationship between two factors, the parent is the factor that affects the influenced factor.

Arc: This is a directional vector drawn from cause to effect, and shows the causal relationship. It is worth noting that R.Graph edges do not form a loop, because the proposed model is acyclic.



a) Interaction between two events

b) Interaction of a variable on an event

c) Interaction between two variables

d) Interaction of an event on a variable

Fig. 2. Different types of causality between two factors in R.Graph

The possible states and factors affecting the R.Graph method, as shown in Fig. 2, are briefly examined in the following.

State 1) The effect of an event on another event

Since the present paper aims to investigate the extent of changes in the problem variables, and also since the problem is considered to be definite, and the event probability is deemed to be 1, the cause and effect events are represented in this state, according to Fig. 2-a, that shows which events influence which other events, or are influenced by them. ${b_{je}}^{e}$ in Fig. 2-a shows the existence of a causal relationship between events j and e, which takes values of zero and one. If ${b_{je}}^{e}$ is one, it shows the existence of causality, otherwise, it indicates the absence of such a relationship.

State 2) The effect of a variable on an event

Similar to the first state, according to Fig. 2-b, it can be determined which events are caused by changes in one variable, in which ${b_{ie}}^{v}$ indicates the existence of a causal relationship between the i −th variable and e −th event; this takes zero and one values.

State 3) The effect of one variable on another variable

In this state, according to Fig. 2-c, the goal is to examine the change in the variable V_v due to the change in the variable V_i.

Proposition 1. Suppose the changes in V_i and V_v are called ΔV_i and ΔV_v, respectively. Now, if V_v is considered as a function of the variable V_i, we will have:

$$\Delta V_v = V_v(V_i + \Delta V_i) - V_v(V_i) \tag{11}$$

Eq. (11) can be called the ‘change rate’ to understand the changes better. In this study, the change rate of a variable is called the risk of that variable, which is generally shown by R. Now, if we write the change rate of V_v (risk of V_v) according to the change rate of V_i (risk of V_i), we have:

$$R(V_v|V_i) = \frac{V_v(V_i \times (1 + R(V_i)))}{V_v(V_i)} - 1 \tag{12}$$

where $R(V_v|V_i)$ indicates the amount of V_v risk due to the existence of the risk in V_i. In this relation, the positive value of $R(V_v|V_i)$ indicates that by increasing the risk of V_i, the risk of V_v also increases (positive correlation), while the negative values indicate that increasing the risk of V_i reduces the risk of V_v (negative correlation).

Proof. *By dividing ΔV_v by $V_v(V_i)$, the growth rate or the risk of V_v is obtained, and we have:*

$$R(V_v|V_i) = \frac{\Delta V_v}{V_v(V_i)} = V_v(V_i + \Delta V_i) - 1$$

If $V_v(V_i + \Delta V_i)$ is also written as a growth rate, i.e., $V_v(V_i(1 + R(V_i)))$, Eq. (12) is proven.■

An important real-world problem is caused by lack of accurate knowledge of the V_v function in terms of V_i, especially in cases where there is a low probability of occurrence in the changes of various factors. Hence, there is often not enough data to estimate the functions of the intended variables. Generally, the V_v function is either linear or nonlinear. However, in the real world, the relationships of many variables, such as values of profit and cost, can be considered as linear. Since it is assumed in this paper that all data are obtained from experts, an approximate linear method for determining the risk of V_v with respect to V_i risk is presented in the following.

Definition 4. Let the function V_v be assumed to be linear in terms of V_i. If the unit risk of V_v is specified in terms of V_i risk, then we have:

$$R(V_v|V_i) = \alpha_{iv} R(V_i) \tag{13}$$

where α_{iv} indicates the amount of risk V_v per unit increase or 100% increase in the risk of V_i, which can be obtained according to experts’ opinions. It is worth noting that in this article, all variables are considered continuous and definite, and if the nature of the variable is probabilistic in the real world, its expected value can be entered into the problem.

State 4) The effect of an event on one variable

In this state, according to Fig. 2-d and assuming the model to be non-probabilistic, it can be said that if E_j occurs as a parent of the variable V_v, V_v grows to a constant and definite amount.

Definition 5. If the risk of the variable V_v due to the occurrence of E_j is I_{jv}, then we have:

$$R\left(V_v|E_j\right) = I_{jv} \tag{14}$$

State 5) The effect of several factors on another variable

Definition 6. Suppose that a set of $\acute{V}$ variables and $\acute{E}$ events affects a specific variable, V_v, and $i = 1, \dots, \acute{V}, j = 1, \dots, \acute{E}$ (Fig. 3); now, if the purpose is to investigate the change rate (risk) of the variable V_v in terms of all these factors, assuming all the factors are independent, we have:

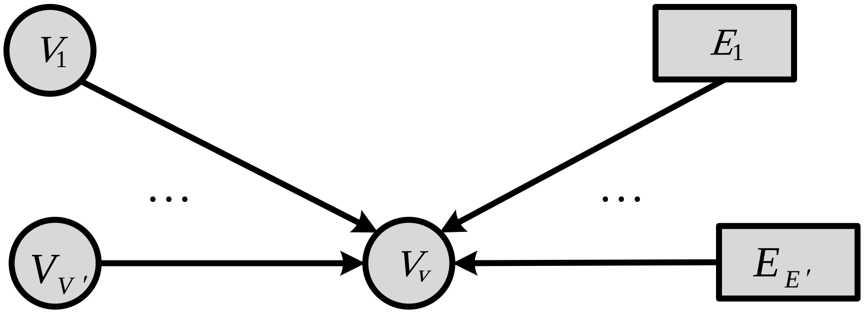


Fig. 3. The effect of different factors on a variable

where $Par(V_v)$ represents all parents of V_v, $R(V_i)$ is the risk of the $i-$th variable and $R\left(V_v|Par(V_v)\right)$ is the change rate (risk) due to changes in or occurrence of $Par(V_v)$.

Now, a separate parent can be assumed for the $Par(V_n)$ members which can be seen in Fig. 4. In this state, Eq. (15) can be generally written as follows:

$$R\left(V_v|Par(V_v)\right) = \sum_{i=1}^{\acute{V}} \alpha_{iv} R\left(V_i|Par(V_i)\right) + \sum_{j=1}^{\acute{E}} I_{jv} \tag{16}$$

In Eq. (16), the risk of the variable V_v was calculated according to its parent. However, we can determine the risk of the variable V_v relative to the risk of an influential variable.

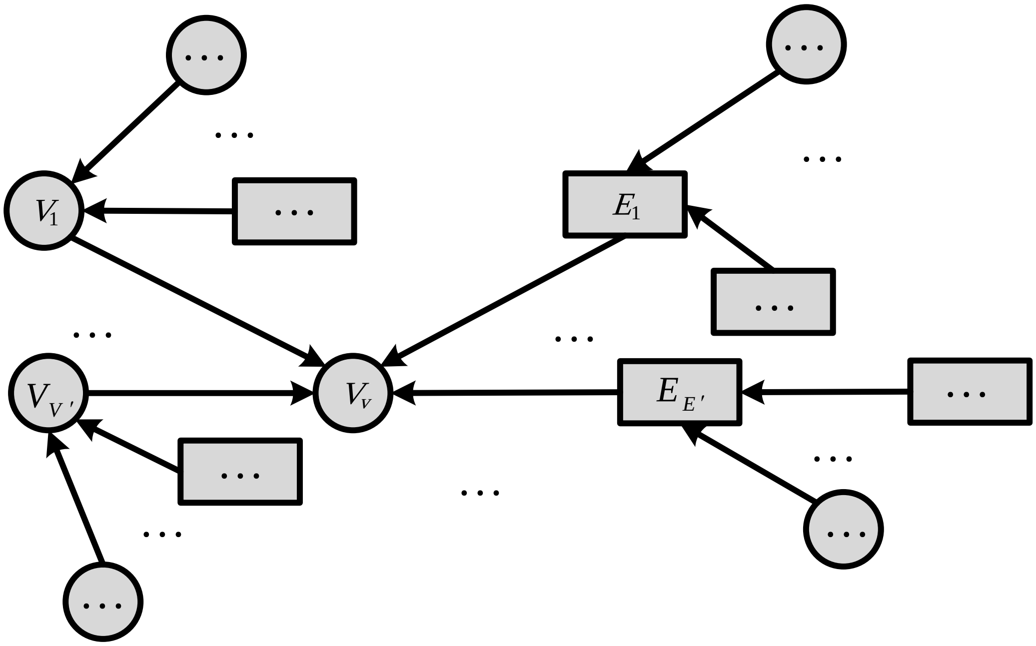


Fig. 4. A typical R.Graph diagram

Definition 7. If we want to define the risk of the variable V_v relative to its influential variable V_i, namely $R(V_v|V_i)$, we will have:

$$\begin{cases} R(V_v|V_i) = \alpha_{iv}R(V_i) + \sum_{l=1}^{L} \alpha_{lv}R(V_l|V_i) + \sum_{k=1}^{K} I_{kv} & V_i \epsilon Par(V_v) \\ R(V_v|V_i) = \sum_{l=1}^{L} \alpha_{lv}R(V_l|V_i) + \sum_{k=1}^{K} I_{kv} & V_i \notin Par(V_v) \end{cases} \tag{17}$$

where V_l represents the variables that are directly or indirectly affected by V_i; I_{kv} shows the effect of events on V_v that are the parents of V_v, and V_i affects their occurrence. Consequently, from Eq. (17), we have:

$$R(V_v|V_v) = 0 \tag{18}$$

Moreover, from Eq. (17), it can be argued that if V_i does not affect V_v in any way, we have:

$$R(V_v|V_i) = 0 \tag{19}$$

Definition 8. The risk of the variable V_v can be defined according to the desired event E_j, i.e., $R\left(V_v|E_j\right)$ as follows:

$$\begin{cases} R\left(V_v|E_j\right) = I_{jv} + \sum_{k=1}^{K} I_{kv} + \sum_{l=1}^{L} \alpha_{lv}R\left(V_l|E_j\right) & E_j \epsilon Par(V_v) \\ R\left(V_v|E_j\right) = \sum_{k=1}^{K} I_{kv} + \sum_{l=1}^{L} \alpha_{lv}R\left(V_l|E_j\right) & E_j \notin Par(V_v) \end{cases} \tag{20}$$

In the above relation, I_{kv} shows the effect of events on V_v, which is the parent of V_v, and also shows that E_j affects their occurrences. V_l also indicates variables directly or indirectly affected by E_j. On the other hand, it can be said that if E_j does not affect V_v in any way, we have:

$$R\left(V_v|E_j\right)=0 \tag{21}$$

After calculating the risk value for each variable, the new value of each variable can be updated using Definition 9.

Definition 9. Suppose the initial value of the variable V_v is denoted by ${V_v}^{old}$; now, if the new value of V_v is displayed as ${V_v}^{new}$, according to the risk value $R\left(V_v|Par(V_v)\right)$, its value is obtained as follows:

$${V_v}^{new}=\left(1+R\left(V_v|Par(V_v)\right)\right){V_v}^{old} \tag{22}$$

The R.Graph data can be displayed through the R.Graph matrix as follows.

Definition 10. Assume that the whole problem includes V variables and E events; the basic values of the effectiveness of the variables (for 100% risk) and the events can be displayed by the R.Graph matrix which is denoted by $R_{R.Graph}$. For simplicity, the $R_{R.Graph}$ may be defined as:

$$R_{R.Graph}=\begin{bmatrix} V-V & V-E \\ E-V & E-E \end{bmatrix}, \tag{23}$$

where the R.Graph matrix consists of 4 separate sub-matrices: $V-V$, $V-E$, $E-V$, and $E-E$. These are defined as follows:

$$V-V=\begin{array}{c|cccccc} & \boldsymbol{V_1} & \boldsymbol{V_2} & \dots & \boldsymbol{V_v} & \dots & \boldsymbol{V_V} \\ \hline \boldsymbol{V_1} & 0 & \alpha_{12} & \dots & \alpha_{1v} & \dots & \alpha_{1V} \\ \boldsymbol{V_2} & \alpha_{21} & 0 & \dots & \alpha_{2v} & \dots & \alpha_{2V} \\ \dots & \dots & \dots & 0 & \dots & \dots & \dots \\ \boldsymbol{V_v} & \alpha_{v1} & \alpha_{v2} & \dots & 0 & \dots & \alpha_{vV} \\ \dots & \dots & 0 & \dots & \dots & 0 & \dots \\ \boldsymbol{V_V} & \alpha_{V1} & \alpha_{V2} & 0 & \alpha_{Vv} & \dots & 0 \end{array}, v=1,\dots V, \forall i=1,\dots,V, \alpha_{iv}\,\epsilon\mathbb{R}, \tag{24}$$

$$V-E=\begin{array}{c|cccccc} & \boldsymbol{E_1} & \boldsymbol{E_2} & \dots & \boldsymbol{E_e} & \dots & \boldsymbol{E_E} \\ \hline \boldsymbol{V_1} & {b_{11}}^v & {b_{12}}^v & \dots & {b_{1e}}^v & \dots & {b_{1E}}^v \\ \boldsymbol{V_2} & {b_{21}}^v & {b_{22}}^v & \dots & {b_{2e}}^v & \dots & {b_{2E}}^v \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \boldsymbol{V_v} & {b_{v1}}^v & {b_{v2}}^v & \dots & {b_{ve}}^v & \dots & {b_{vE}}^v \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \boldsymbol{V_V} & {b_{V1}}^v & {b_{V2}}^v & \dots & {b_{Ve}}^v & \dots & {b_{VE}}^v \end{array}, v=1,\dots V, e=1,\dots,E, \forall i=1,\dots,V,\ {b_{ie}}^v\epsilon\{0,1\}, \tag{25}$$

$$E-V=\begin{array}{c|cccccc} & \boldsymbol{V_1} & \boldsymbol{V_2} & \dots & \boldsymbol{V_v} & \dots & \boldsymbol{V_V} \\ \hline \boldsymbol{E_1} & I_{11} & I_{12} & \dots & I_{1v} & \dots & I_{1V} \\ \boldsymbol{E_2} & I_{21} & I_{22} & \dots & I_{2v} & \dots & I_{2V} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \boldsymbol{E_e} & I_{e1} & I_{e2} & \dots & I_{ev} & \dots & I_{eV} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \boldsymbol{E_E} & I_{E1} & I_{E2} & \dots & I_{Ev} & \dots & I_{EV} \end{array}, v=1,\dots V, e=1,\dots,E, \forall j=1,\dots,E,\ I_{jv}\,\epsilon\mathbb{R}, \tag{26}$$

$$E-E=\begin{array}{c}\\ \boldsymbol{E_1}\\ \boldsymbol{E_2}\\ \cdots\\ \boldsymbol{E_e}\\ \cdots\\ \boldsymbol{E_E}\end{array}\begin{array}{c}\begin{array}{cccccc}\boldsymbol{E_1} & \boldsymbol{E_2} & \ldots & \boldsymbol{E_e} & \ldots & \boldsymbol{E_E}\end{array}\\ \begin{bmatrix}0 & {b_{12}}^{e} & \ldots & {b_{1e}}^{e} & \ldots & {b_{1E}}^{e}\\ {b_{21}}^{e} & 0 & \ldots & {b_{2e}}^{e} & \ldots & {b_{2E}}^{e}\\ \ldots & \ldots & 0 & \ldots & \ldots & \ldots\\ {b_{e1}}^{e} & {b_{e2}}^{e} & \ldots & 0 & \ldots & {b_{eE}}^{e}\\ \ldots & \ldots & \ldots & \ldots & 0 & \ldots\\ {b_{E1}}^{e} & {b_{E2}}^{e} & 0 & {b_{Ee}}^{e} & \ldots & 0\end{bmatrix}\end{array},\ e=1,\ldots,E,\ \forall j=1,\ldots,E,\ {b_{je}}^{e}\epsilon\{0,1\}. \qquad (27)$$

where the $V-V$ matrix describes the impact of variables' risks on other variables; the $V-E$ matrix defines the impact of variables on events; the $E-V$ matrix describes the impact of events' risks on variables; and the impact of events' risks on other events are defined by the $E-E$ matrix. In the $V-V$ matrix, α_{iv} shows the risk of the v-th variable per 100% increase in risk of the i-th variable. Since the graph is acyclic, if α_{iv} adopts a value, we will have $\alpha_{vi}=0$. In the $E-V$ matrix, I_{jv} indicates the risk of the v-th variable due to the occurrence of the j-th event. Finally, in the $E-E$ and $V-E$ matrices, ${b_{je}}^{e}$ and ${b_{ie}}^{v}$ indicate how the occurrence of e-th event is affected by the occurrence of the j-th event and i-th variable, respectively. If ${b_{je}}^{e}$ and ${b_{ie}}^{v}$ take values of one, indicate that the occurrence of the e-th event is affected by the j-th event and i-th variable. If ${b_{je}}^{e}$ and ${b_{ie}}^{v}$ are zero, it indicates that there is no effect. Here, also because the graph is acyclic, if ${b_{je}}^{e}=1$ and ${b_{ie}}^{v}=1$, we have ${b_{je}}^{e}=0$ and ${b_{ei}}^{v}=0$.

Example 1. Assume that the R.Graph matrix corresponds to Fig. 5;

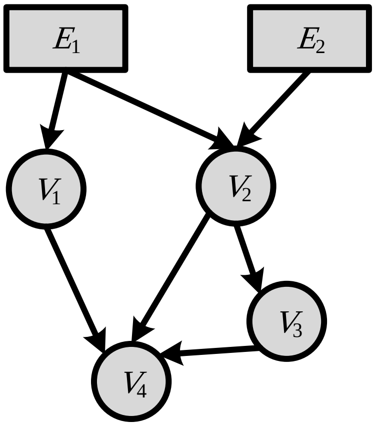


Fig. 5. The R.Graph diagram of factors in Example 1

$$R^{R.Graph}=\begin{array}{c}\\ \boldsymbol{V_1}\\ \boldsymbol{V_2}\\ \boldsymbol{V_3}\\ \boldsymbol{V_4}\\ \boldsymbol{E_1}\\ \boldsymbol{E_2}\end{array}\begin{array}{c}\begin{array}{cccccc}\boldsymbol{V_1} & \boldsymbol{V_2} & \boldsymbol{V_3} & \boldsymbol{V_4} & \boldsymbol{E_1} & \boldsymbol{E_2}\end{array}\\ \left[\begin{array}{cc}\begin{bmatrix}0 & 0 & 0 & -0.5\\ 0 & 0 & 0.2 & 0.3\\ 0 & 0 & 0 & 0.6\\ 0 & 0 & 0 & 0\end{bmatrix} & \begin{bmatrix}0 & 0\\ 0 & 0\\ 0 & 0\\ 0 & 0\end{bmatrix}\\ \begin{bmatrix}-0.3 & 0.4 & 0 & 0\\ 0 & -0.25 & 0 & 0\end{bmatrix} & \begin{bmatrix}0 & 0\\ 0 & 0\end{bmatrix}\end{array}\right]\end{array}$$

The risk values of each variable can be computed as follows:

$Par(V_1) = \{E_1\} \rightarrow R(V_1) = I_{11} = -0.3$

$Par(V_2) = \{E_1, E_2\} \rightarrow R(V_2) = I_{12} + I_{21} = 0.4 - 0.25 = 0.15$

$Par(V_3) = \{V_2\} \rightarrow R(V_3) = \alpha_{23}R(V_2) = 0.2 \times 0.15 = 0.03$

$Par(V_4) = \{V_1, V_2, V_3\} \rightarrow R(V_4) = \alpha_{14}R(V_1) + \alpha_{24}R(V_2) + \alpha_{34}R(V_3) = -0.5 \times -0.3\ + 0.3 \times 0.15 +\ 0.6 \times 0.03 = 0.213$

4.1.2. Consistency checking

As mentioned in the introduction, in some cases, the only available data is expert knowledge. However, experts can make errors in judgment, which may lead to ineffective use and transfer of expert knowledge. Human decision-making has been shown to be inconsistent both between and within individuals. There are multiple possible sources for this inconsistency [14]: the problem type; the judge's decision criteria; uncertainty in the judge's knowledge; or randomness in judgments. Decision-making by experts may also exhibit random variation in situations with similar alternatives [14]; there is also the possibility of systematic variation, depending on the amount of time available for experts to make choices [14]. This is also a factor when decision processes are context-dependent. In small samples with few experts, even minor inconsistency can cause large deviations in terms of commercialization choices [14].

One of the things that should be considered in the R.Graph method is to check the inconsistency of the evaluations. On this basis, after obtaining the results through the R.Graph method, the following condition should be considered for each variable:

$$R(V_v)^{min} \leq R\big(V_v|Par(V_v)\big) \leq R(V_v)^{max} \tag{28}$$

where $R(V_v)^{min}$ and $R(V_v)^{max}$ are the lowest and highest possible risk values that $R\big(V_v|Par(V_v)\big)$ can take, respectively.

4.1.3. Acceptable risk

In the proposed method of R.Graph, if there is a risk in a parent, the risk is passed on to its offspring, which increases the risk values of the downstream variables. Since one of the goals of the R.Graph method is to identify events that affect critical variables and plan to reduce their risk, high risk demands greater efforts in decreasing the risk. Therefore, in some decision-making problems, decision-makers accept some level of risk due to organizational goals and the degree of risk-taking, which is called ‘acceptable risk’ (AR) in the literature [35, 36].

In this paper, the acceptance level of risk and changes in a variable is defined as the percentage change due to events or changes in the desired variable that can be accepted and compensated by the relevant organization which are not included in the calculations. This can be expressed as:

Acceptable risk = Risk-taking degree + Risk-compensation degree

In the R.Graph method, some of the risk levels of each variable can therefore be considered acceptable. However, since the risk value of one variable depends on the risk values of other variables, the acceptance and compensation of some risks affects the risks of other variables, so the risk values of each variable should be calculated by considering the acceptable risk of the variables. Therefore if the AR value is defined as a percentage between 0 and 100, each risk value can be modified based on Definition 11.

Definition 11. Assume that the risk-taking of the i-th variable is shown by ${AR_i}^v$, considering the level of risk-taking, Eq. (16) can be rewritten as follows:

$$R\big(V_v|Par(V_v)\big) = \left(\sum_{i=1}^{\acute{V}} \alpha_{iv} R\big(V_i|Par(V_i)\big) + \sum_{j=1}^{\acute{E}} I_{jv}\right) \times (1 - {AR_v}^v) \tag{29}$$

where the values of acceptable risk are considered simultaneously for inputs and outputs, and $1 - {AR_v}^v$is the percentage of risks not accepted and entered into the problem. Generally, the matrix of acceptable risk for V variables, which is displayed by AR^V, can be defined as follows:

$$AR^V = [{AR_1}^v, .., {AR_v}^v \dots, {AR_V}^v] \tag{30}$$

where $0 \leq {AR_v}^v \leq 1$.

Example 2. Considering Example 1 and the acceptable risk values , the risk values of each variable in Example 1 can be calculated as follows:

$AR^V = [{AR_1}^v = 0.3, {AR_2}^v = 0,\ {AR_3}^v = 0.5, {AR_4}^v = 0.2]$

$R(V_1) = I_{11}(1 - {AR_1}^v) = -0.3(1 - 0.3) = -0.21$

$R(V_2) = (I_{12} + I_{21})(1 - {AR_2}^v) = (0.4 - 0.25)(1 - 0) = 0.15$

$R(V_3) = \alpha_{23} R(V_2)(1 -\ {AR_3}^v) = 0.2 \times 0.15 \times (1 - 0.5) = 0.015$

$R(V_4) = \big(\alpha_{14} R(V_1) + \alpha_{24} R(V_2) + \alpha_{24} R(V_3)\big) \times (1 - {AR_4}^v) = (-0.5 \times -0.21\ + 0.3 \times 0.15 +\ 0.6 \times 0.015) \times (1 - 0.2) = 0.1272$

4.1.4. Determining pessimistic and optimistic risk values

In some decision-making and risk analysis problems, the decision-maker is interested to know the value of the highest and lowest risks that will be experienced in each variable, terming them pessimistic and optimistic values, respectively. Since the risk values of each variable or event on a specific variable are either positive or negative, Proposition 2 can be formulated.

Proposition 2. The maximum and minimum amount of risk of a variable can be determined as follows:

$$\begin{cases} maxR(V_v) = \sum_{i=1}^{\acute{V}} {\alpha_{iv}}^- minR(V_i) + \sum_{i=1}^{\acute{V}} {\alpha_{iv}}^+ maxR(V_i) + \sum_{j=1}^{\acute{E}} {I_{jv}}^+ & maxR(V_v) \geq 0 \\ minR(V_v) = \sum_{v=1}^{\acute{V}} {\alpha_{vn}}^- maxR(V_i) + \sum_{i=1}^{\acute{V}} {\alpha_{iv}}^+ minR(V_i) + \sum_{j=1}^{\acute{E}} {I_{jv}}^- & minR(V_v) \leq 0 \end{cases} \tag{31}$$

where $maxR(V_i)$ shows the highest value of risk (pessimistic risk) and $minR(V_n)$ shows the lowest amount of risk (optimistic risk) of the variable V_i. Also, in these relations, ${I_{jv}}^+$ and ${I_{jv}}^-$ represent the effects of event risks on variables which are positive and negative, respectively. Moreover, ${\alpha_{iv}}^+$ and ${\alpha_{iv}}^-$ indicate positive and negative values, which are defined as follows:

$$\begin{cases} {\alpha_{iv}}^+ = \begin{cases} \alpha_{iv} & if\ \alpha_{iv} > 0 \\ 0\ otherwise \end{cases} \\ {\alpha_{iv}}^- = \begin{cases} \alpha_{iv} & if\ \alpha_{iv} < 0 \\ 0\ otherwise \end{cases} \\ {I_{jv}}^+ = \begin{cases} I_{jv}\ if I_{jv} > 0 \\ 0\ otherwise \end{cases} \\ {I_{jv}}^- = \begin{cases} I_{jv}\ if I_{jv} < 0 \\ 0\ otherwise \end{cases} \end{cases} \tag{32}$$

Proof. *For $R(V_v)$ to reach its maximum value, namely $maxR(V_v)$, only sentences with positive or zero values must be included. If $R(V_v)$ is itself affected by other events and variables, only its positive sentences should be considered. Hence, only positive values of I_{jv}, i.e., ${I_{jv}}^+$, are entered into the $maxR(V_v)$ calculation. However, since the values of α_{iv} are multiplied by $R(V_i)$, this multiplication is positive when either both α_{iv} and $R(V_i)$ are negative, or both are positive. Thus, the $maxR(V_v)$ value is obtained. Similarly, the relation of $minR(V_v)$ can be proven.*■

Example 3. Considering Example 1, optimistic and pessimistic values for each of the variable can be calculated as follows:

$$\begin{cases} maxR(V_1) = 0 \\ minR(V_1) = {I_{11}}^- = -0.3 \end{cases}$$

$$\begin{cases} maxR(V_2) = {I_{21}}^- = -0.25 \\ minR(V_2) = {I_{12}}^+ = 0.4 \end{cases}$$

$$\begin{cases} maxR(V_3) = {\alpha_{23}}^+ maxR(V_2) = 0.2 \times 0.15 = 0.03 \\ minR(V_3) = 0 \end{cases}$$

$$\begin{cases} maxR(V_4) = {\alpha_{14}}^- minR(V_1) + {\alpha_{24}}^+ maxR(V_2) + {\alpha_{24}}^+ maxR(V_3) = 0.213 \\ minR(V_4) = 0 \end{cases}$$

4.1.5. Identifying critical factors

One of the goals of cause and effect methods, including the proposed R.Graph method, is to identify the events or variables with the most significant impact on other variables, as considered by an organization. Indeed, the organization or managers can identify these critical factors and plan to reduce related negative consequences. The following outlines the prioritization of factors in the proposed R.Graph method.

Proposition 3. Assume that the total number of variables is V, and the total number of events is E; then, the relative importance of factors is obtained from the following relation:

$$\begin{cases} {w_i}^v = \frac{\sum_{v=1}^{V} |R(V_v|V_i)| + |R(V_i)|}{\sum_{i=1}^{V} \sum_{v=1}^{V} (|R(V_v|V_i)| + |R(V_i)|) + \sum_{j=1}^{E} \sum_{v=1}^{V} \left|R\left(V_v|E_j\right)\right|} \\ {w_j}^e = \frac{\sum_{v=1}^{V} \left|R\left(V_v|E_j\right)\right|}{\sum_{i=1}^{V} \sum_{v=1}^{V} (|R(V_v|V_i)| + |R(V_i)|) + \sum_{j=1}^{E} \sum_{v=1}^{V} \left|R\left(V_v|E_j\right)\right|} \end{cases} \tag{33}$$

where ${w_i}^v$ shows the weight of the i-th variable and ${w_j}^e$ shows the weight of j-th event among all factors.

Proof. *The change rates in the risk of all variables can be written, considering the i-th variable, as follows:*

$\sum_{v=1}^{V} |R(V_v|V_i)| + |R(V_i)|$

Also, the change rates of the risk of all variables can be obtained, considering the importance of the j-th event, as follows:

$\sum_{j=1}^{E} \left|R\left(V_v|E_j\right)\right|$

To obtain the significance of the i-th variable or the importance of the j-th event among V variables and E events, it must be divided by the sum of the changes. In this way, Eq. (33) can be proven.■

Example 4. Suppose the causal is in the form of Fig. 5, and its binary display, which is indicated by arrows, can be seen in Fig. 6. To find the effect of the variable V_3 on the problem, it is necessary to find the effects of the variable V_3 on other variables, and then remove the variable V_3 from the problem. This is shown by drawing the yellow lines in Fig. 6, stating that V_3 removal only affects the variable V_4. Now, the weight of the variable V_3 can be determined as follows:

$|R(V_4|V_3)| + |R(V_3)| = 0.048$

$\sum_{i=1}^{V} \sum_{v=1}^{V} (|R(V_v|V_i)| + |R(V_i)|) + \sum_{j=1}^{E} \sum_{v=1}^{V} \left|R\left(V_v|E_j\right)\right| = 2.405$

${w_4}^v = \frac{0.048}{2.7} = 0.0195$

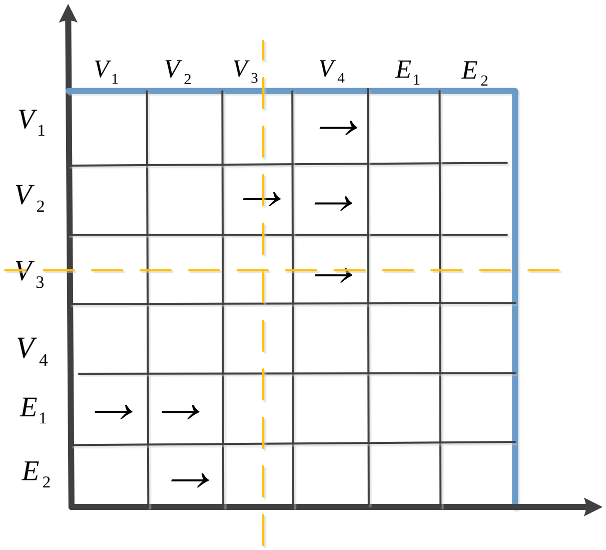


Fig. 6. Variable V_3 removal and the interaction of factors in Example 1

4.1.6. Sensitivity analysis

This section examines how to find the sensitivity of the changes in one variable over other problem variables.

Proposition 4. If the amount of the intended change to the sensitivity analysis of the variable v (for a 100% increase in the risk of V_i) is called ΔV_{iv}, then the sensitivity of the whole problem over the variable V_i will be obtained as follows:

$$S^{vi}\big|\Delta V_{iv} = \sum_{v=1}^{V} R(V_v|V_i + \Delta V_{iv}\,) - \sum_{v=1}^{V} R(V_v|V_i) \tag{34}$$

where $S^{vi}\big|\Delta V_{iv}$ indicates problem sensitivity (total changed risk) to the i-th variable on the v-th variable, considering ΔV_{iv}, where ΔV_{iv} can be positive or negative. Also, $\sum_{v=1}^{V} R(V_v|V_i + \Delta V_{iv})$ indicates the sum of the V_v risk calculation for V_i among V variables, assuming the value of ΔV_{iv} for the variables risk calculation with a 100% change in V_i. Similarly, sensitivity analysis can be performed on a specific event as follows.

Proposition 5. If the sensitivity change of the j-th event over the v-th variable is called ΔV_{jv}, then we will have:

$$S^{ej}\big|\Delta V_{jv} = \sum_{v=1}^{V} R\big(V_v|E_j + \Delta V_{jv}\,\big) - \sum_{v=1}^{V} R\big(V_v|E_j\big) \tag{35}$$

where $S^{ej}\big|\Delta V_{jv}$ shows the sensitivity of the problem over the j-th event for ΔV_{jv}, and $\sum_{v=1}^{V} R\big(V_v|E_j + \Delta V_{jv}\,\big)$ shows the risk calculation of V_v for the event E_j among V variables, assuming the value of ΔV_{jv} indicates more risk due to the E_j event.

Example 5. Considering the R.Graph matrix in Example 1, and assuming $\Delta V_{jv} = \Delta V_{iv} = 0.2, \forall i, j$, the sensitivity of the problem to all factors will thus be as follows:

For Event 1:

$R(V_1|E_1 + 0.2\,) = I_{11} + 0.2 = -0.3 + 0.2 = -0.1 \;\; \& \, R(V_1|E_1) = -0.3$

$R(V_2|E_1 + 0.2\,) = I_{12} + 0.2 = 0.4 + 0.2 = 0.6 \;\; \& \, R(V_2|E_1) = 0.4$

$R(V_3|E_1 + 0.2\,) = \alpha_{23} R(V_2|E_1 + 0.2\,) = 0.2 \times 0.6 = 0.12 \;\; \& \, R(V_3|E_1) = 0.08$

$R(V_4|E_1 + 0.2\,) = \alpha_{14} R(V_1|E_1 + 0.2\,) + \alpha_{24} R(V_2|E_1 + 0.2\,) + \alpha_{34} R(V_3|E_1 + 0.2\,) = -0.5 \times -0.1 \; + 0.3 \times 0.6 + \; 0.6 \times 0.12 = 0.302 \;\; \& \, R(V_4|E_1) = 0.318$

Therefore, according to Eq. (35), we have:

$S^{e1}|0.2 = \sum_{v=1}^{4} R(V_v|E_1 + 0.2\,) - \sum_{v=1}^{4} R(V_v|E_1) = 0.424$

For Event 2:

$R(V_1|E_2 + 0.2\,) = 0 \;\; \& \, R(V_1|E_2) = 0$

$R(V_2|E_2 + 0.2\,) = I_{21} + 0.2 = -0.25 + 0.2 = -0.05 \;\; \& \, R(V_2|E_2) = -0.25$

$R(V_3|E_2 + 0.2\,) = \alpha_{23} R(V_2|E_2 + 0.2\,) = 0.2 \times -0.05 = -0.01 \;\; \& \, R(V_3|E_2) = -0.05$

$R(V_4|E_2 + 0.2\,) = \alpha_{14} R(V_1|E_2 + 0.2\,) + \alpha_{24} R(V_2|E_2 + 0.2\,) + \alpha_{34} R(V_3|E_2 + 0.2\,) = 0 \; + 0.3 \times -0.05 + \; 0.6 \times -0.01 = -0.021 \;\; \& \, R(V_4|E_2) = -0.105$

Therefore, according to Eq. (35), we have:

$S^{e2}|0.2 = \sum_{v=1}^{4} R(V_v|E_1 + 0.2\,) - \sum_{v=1}^{4} R(V_v|E_2) = 0.324$

Other factor sensitivities are obtained in a similar way, using Eq. (34) as follows:

$S^{v1}|0.2 = \sum_{v=1}^{4} R(V_v|V_1 + 0.2\,) - \sum_{v=1}^{4} R(V_v|V_1) = -0.06$

$S^{v2}|0.2 = \sum_{v=1}^{4} R(V_v|V_2 + 0.2\,) - \sum_{v=1}^{4} R(V_v|V_2) = 0.078$

$S^{v3}|0.2 = \sum_{v=1}^{4} R(V_v|V_3 + 0.2) - \sum_{v=1}^{4} R(V_v|V_3) = -0.006$

$S^{v4}|0.2 = \sum_{v=1}^{4} R(V_v|V_4 + 0.2\,) - \sum_{v=1}^{4} R(V_v|V_4) = 0$

showing that by increasing the constant value per input risks, the problem is more sensitive to risk changes in E_1.

4.2. The risk analysis framework using the proposed R.Graph method

As mentioned in the introduction, the purpose of developing the R.Graph approach is to provide a cause and effect model using expert knowledge. In fact, it aims at analyzing risk and changes in important organizational parameters, based on risk factors with a low probability of occurrence, to provide preventive solutions and relative preparedness. The way of modeling in R.Graph method and its mathematical relations were presented in Section 4.1. Additionally, different cases of the risk analysis were considered, such as considering acceptable risk, optimistic and pessimistic situations, the importance of factors, and sensitivity analysis. The following section aims to provide a group risk analysis framework by experts, based on the proposed R.Graph method, and is summarized as follows:

Phase I: Data preparation

Step zero. *Identifying the set of events and variables affecting each other, and the degree of acceptable risk.*

In this step, the organization's intended variables are considered, examined, and determined according to organizational purposes. In addition to the factors leading to changes in intended variables or other events, the organization also wants to investigate how these effects are specified. In this step, the interrelations between variables and events are determined using expert opinions and by a moderator. Then, a graph of causes and effects is drawn, from which the event-variable matrix (i.e., $E-V$) and the event-event matrix (i.e., $E-E$) can be created. Additionally, the experts are asked to determine the effects and risks of events on variables ($E-V$ matrix) and the effects of variables on variables ($V-V$ matrix) by defining a specific percentage. The sample questionnaire for obtaining the $E-V$ and $V-V$ matrices is provided in Appendix 1. It is worth noting that, since R.Graph relations are developed based on the unit value of these changes, after determining the impact percentage by experts, the evaluation values are converted to unit values in terms of percentage (dividing by 100).

Finally, according to organizational macro policies, goals, and perspectives, values are determined relating to the acceptability of risks of variables. A sample questionnaire for obtaining acceptable risk values is shown in Appendix 2.

Step 1. *Aggregating the $E-V$ and $V-V$ matrices and determining the R.Graph matrix*

In this step, the R.Graph risk matrix can be determined, according to the 4 matrices $E-E$, $E-V$, $V-E$, and $V-V$. It should be noted that evaluation values obtained directly by each expert (which can contain continuous values) occur in matrices $V-V$ and $E-V$. These represent the impacts of variables and events on other variables. Since the values of these two matrices may be different for each expert's evaluations, the aggregated values of all the expert opinions must first be calculated for each of these two matrices.

Let us denote the $E-V$ and $V-V$ matrices of the t-th expert as $(E-V)^t$ and $(V-V)^t$. If there are T experts in the problem, the aggregated values of these two matrices are determined through the HWA operator. Let us consider $(V-V)^t = \left[{\alpha_{ij}}^t\right]$ and $(E-V)^t = \left[{I_{ij}}^t\right]$; if we denote the aggregated matrices of $(V-V)^t$ and $(E-V)^t$ as $(V-V)^T$ and $(E-V)^t$, using the HWA operator, we have:

$$(V-V)^T = HWA((V-V)^1, (V-V)^2, \dots, (V-V)^T) = \left[\sum_{t=1}^{T} \acute{w}_t {\acute{\alpha}_{\iota\jmath}}^t\right] \tag{36}$$

$$(E-V)^T = HWA((V-V)^1, (V-V)^2, \dots, (V-V)^T) = \left[\sum_{t=1}^{T} \acute{w}_t \acute{I_{ıȷ}}^{t}\right] \tag{37}$$

where vector $\acute{W} = (\acute{w}_1, \acute{w}_2, \dots, \acute{w}_t)^T$ is the weighting vector associated with OWA, $\acute{\alpha_{ıȷ}}^{t}$ and $\acute{I_{ıȷ}}^{t}$ are the t-th largest of the weighted arguments $Tw_t\alpha_{ij}{}^{t}$and $Tw_tI_{ij}{}^{t}$ $(t = 1,2, \dots, T)$. $W = (w_1, w_2, \dots, w_T)^T$ is the weighting vector of the experts, with $\sum_{i=1}^{n} w_i = 1$ and $w_i \in [0,1]$, and T is the balancing coefficient.

Now the aggregated R.Graph matrix $({R^T}_{R.Graph})$ can be defined based on the $E-E$ and $V-E$ matrices obtained at Step zero. The aggregated matrices $(V-V)^T$ and $(E-V)^T$ may be described as follows:

$${R^T}_{R.Graph} = \begin{bmatrix} (V-V)^T & V-E \\ (E-V)^T & E-E \end{bmatrix} \tag{38}$$

Phase II: Processing

Step 2. *Determining the risk of each variable*

Now, according to the aggregated R.Graph matrix $({R^T}_{R.Graph})$, the risk value of each variable can be obtained through considering the acceptable risk matrice AR^V using Eq. (29) or without considering AR^V by employing Eq. (16).

Step 3. *Calculating the value of pessimistic and optimistic risks*

At this stage, the maximum risk values (pessimistic risks) $maxR(V_v)$ and the lowest risk values (optimistic risks) $minR(V_v)$ are calculated for each variable according to Eq. (31).

Phase III: Consistency checking

Step 4. Consistency checking of risk values

In this step, the risk values obtained without considering AR values are checked against the consistency constraint of Eq. (28). If this condition is not met, the values of the matrices $(V-V)^T$ and $(E-V)^T$ must be revised or adjusted.

Phase IV: Post-processing

Step 5. *Calculating the weights of all variables and events*

In this step, Eq. (33) is used to determine the importance of each factor, whether variable or event.

Step 6. *Sensitivity analysis*

To identify the sensitivity analysis of different factors in their input parameters, considering different values for ΔV_{iv} and ΔV_{jv}, Eqs. (34) and (35) are employed to calculate the sensitivities of the variables and events, respectively.

The R.Graph algorithm is represented in Algorithm 1 and Fig. 7.

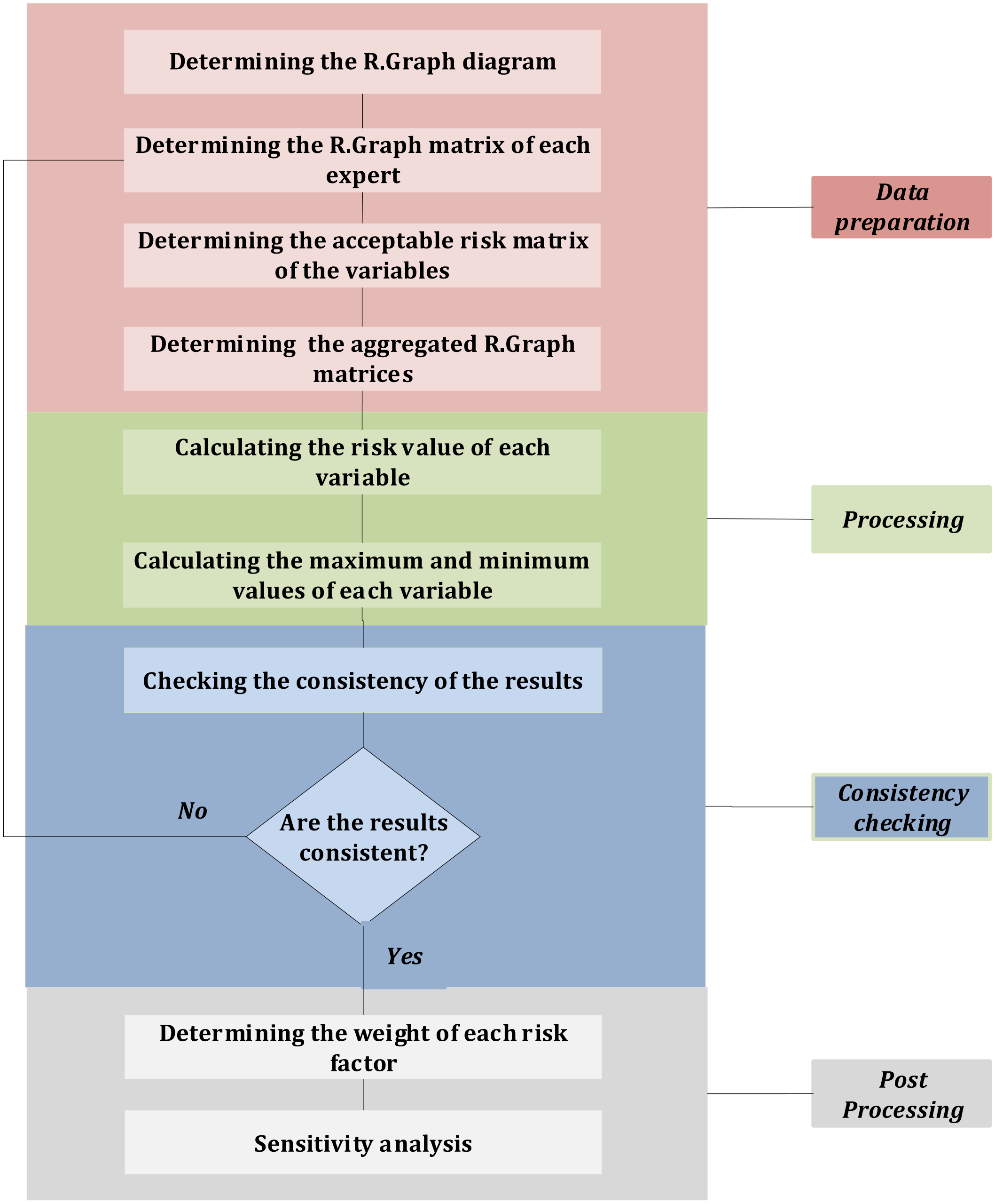


Fig. 7. The R.Graph methodology

```
Algorithm 1: R.Graph inference
Inputs: $R^T{}_{R.Graph}$; $AR^V = [AR_1{}^v, .., AR_v{}^v \dots, AR_V{}^v]$; $\Delta V_{iv}$; $\Delta V_{jv}$;
Outputs: The risk values $(R(V_i)$; The pessimistic and optimistic risk values $(maxR(V_i), minR(V_i))$; the importance weights
of $i$-th variable and $j$-th event $(w_i{}^v, w_j{}^e)$; the sensitivity values of $i$-th variable and $j$-th event $(S^{vi} | \Delta V_{iv}, S^{ej} | \Delta V_{jv})$.
for $i = 1; i \leq V, j = 1; j \leq E$ do
        /*Step 1 */
        for $t = 1; t \leq T$ do
            Calculate the aggegated R.Graph matrix by Eq. (38);
        end
        /* Step 2 */
        Obtaining the risk values of each variable $(R(V_i))$ by Eq. (29) or Eq. (16);
        /* Step 3 */
        Obtaining the pessimistic and optimistic risk values $(maxR(V_i), minR(V_i))$ using Eq. (31)
        /* Step 4 */
        Consistency checking of risk values using Eq. (28)
            if the risks are consistent, go to Step 5.
            else if, revise the R.Graph matrix.
            end
        /* Step 5 */
        Calculate the importance weights of $i$-th variable and $j$-th event $(w_i{}^v, w_j{}^e)$ by Eq. (33);
        /* Step 6 */
        Determine the sensitivity values of $i$-th variable and $j$-th event $(S^{vi} | \Delta V_{iv}, S^{ej} | \Delta V_{jv})$ by Eqs. (34) and (35);
end
```

5. Case study

The COVID-19 epidemic in Iran is part of the worldwide Coronavirus pandemic, which has had various consequences, including social and economic implications, for the entire country. One of the most critical parts of Iran's economy that has been significantly affected by the Coronavirus is the electricity industry. COVID-19 is projected to reduce production volumes and shut down manufacturing, contracting, and consulting units, leaving manufacturing units temporarily closed and costing a large number of jobs [1]. The volume of executive activities will be reduced, and ongoing projects may also be delayed; with the disruption of trade, imports and exports related to the electricity industry will additionally be severely disrupted [1]. The power grid is unstable, and blackouts occur. Delays in the private sector, due to declining production, will lead to the closure and bankruptcy of manufacturers and contractors in the electricity industry, and ultimately the electricity industry economy will suffer direct and indirect losses due to delays in bank payments, social security, and taxes [1]. In this study, the aim is thus to investigate the reduction of profitability of Iran's electricity industry due to the Coronavirus outbreak, and its consequences, over a one-year period.

4 categories of events and 13 variables have been identified in the industry which are directly and indirectly affected by the Coronavirus pandemic, as shown in Table 1. Additionally, the causal relationships of these factors have been identified by relevant experts and drawn into the R.Graph

Diagram (Fig. 8), which led to the determination of the $E - E$ (Table 2) and $V - E$ matrices (Table 3).

The six steps of the proposed methodology (Section 4.2) have been utilized to evaluate the risk of each variable in different scenarios, and risk analysis has been carried out using the R.Graph method.

Table 1. The interacting factors in the analysis of Coronavirus risk in the electricity industry

Index	Variable	Index	Event
$\boldsymbol{V_1}$	Number of key personnel	$\boldsymbol{E_1}$	Coronavirus pandemic
$\boldsymbol{V_2}$	Degree of work difficulty	$\boldsymbol{E_2}$	Personnel refusing to attend the workplace
$\boldsymbol{V_3}$	Environmental health costs	$\boldsymbol{E_3}$	First-degree relatives being infected
$\boldsymbol{V_4}$	Personnel medical expenses	$\boldsymbol{E_4}$	Staff infections
$\boldsymbol{V_5}$	Level of stress	$\boldsymbol{E_5}$	New safety regulations
$\boldsymbol{V_6}$	Percentage of receivables		
$\boldsymbol{V_7}$	Energy sales revenue		
$\boldsymbol{V_8}$	Power branch sales revenue		
$\boldsymbol{V_9}$	Total personnel efficiency		
$\boldsymbol{V_{10}}$	Project delay rate		
$\boldsymbol{V_{11}}$	Total cost		
$\boldsymbol{V_{12}}$	Total income		
$\boldsymbol{V_{13}}$	Total profit		

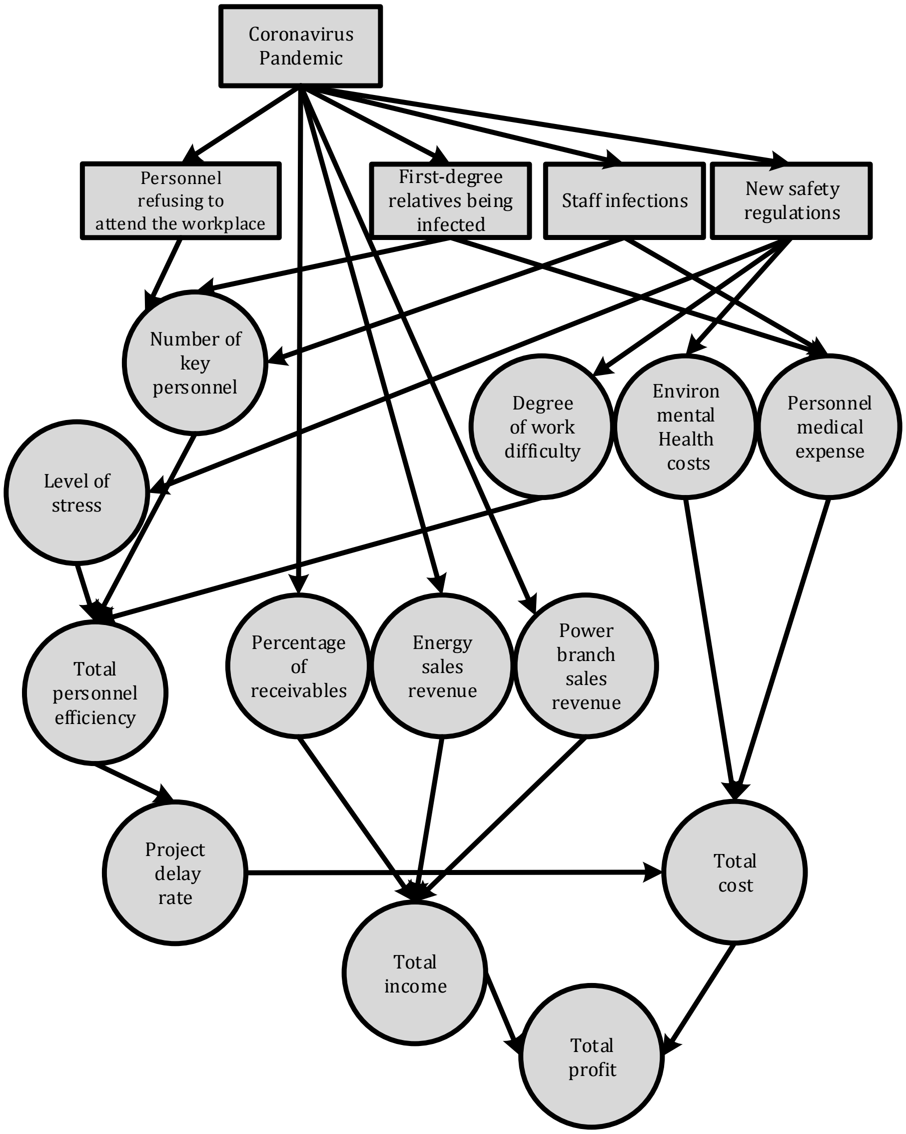


Fig. 8. The R.Graph diagram of the case study

Table 2. The $E-E$ matrix

	E_1	E_2	E_3	E_4	E_5
E_1	0	1	1	1	1
E_2	0	0	0	0	0
E_3	0	0	0	0	0
E_4	0	0	0	0	0
E_5	0	0	0	0	0

Table 3. The $V - E$ matrix

	E_1	E_2	E_3	E_4	E_5
V_1	0	0	0	0	0
V_2	0	0	0	0	0
V_3	0	0	0	0	0
V_4	0	0	0	0	0
V_5	0	0	0	0	0
V_6	0	0	0	0	0
V_7	0	0	0	0	0
V_8	0	0	0	0	0
V_9	0	0	0	0	0
V_{10}	0	0	0	0	0
V_{11}	0	0	0	0	0
V_{12}	0	0	0	0	0
V_{13}	0	0	0	0	0

5.1. Determining the R.Graph and acceptable risk matrices and aggregating expert opinions

In the initial stage, by determining the R.Graph diagram of Fig. 8, two sub-matrices of the R.Graph matrix (i.e. $E - E$ and $V - E$) were first determined in order to obtain the other two matrices, namely the matrices of the event on variable effect ($E - V$) and the variable on variable effect ($V - V$). Three experts from the field of the electricity industry were recruited to cooperate with the study. The participants were then analyzed demographically. Two experts were held doctorates in related fields, while one held a related postgraduate degree. The decision-makers had high levels of experience in the field, ranging from 5 to 25 years. As per the data collected, the decision-makers involved in this study were the researchers from two research centers (namely from a high-capacity power transmission center, and from a group planning and operating power systems).

In order to analyze the risk of each variable, the three experts were asked to specify the impact and risk of potential events on each of the affected variables. They were also asked to estimate the effect (risk) of each variable on other variables, in case of a 100% increase in the effective variable. For example, experts were asked the following question to determine the effect of the event "*new safety regulations*" on the variable "*job difficulty*":

How many percentage points do you think new safety regulations will alter job difficulty?

In order to determine the effects of variable "*personnel medical expenses*" on "*total cost*", the following question was asked:

How many percentage points do you think a 100% increase in personnel medical expenses will alter total cost?

In both types of questions, participants were requested to indicate an increase in the percentage changes with a positive sign, and a decrease with a negative. The questionnaire used for obtaining the $V-V$ and $E-V$ matrices of each expert can be found in Appendix 1. Next, since the $V-V$ and $E-V$ matrices in the R.Graph method were developed based on the unit value of the changes, after determining the percentage impacts by experts, the evaluation values were converted to unit values in terms of percentage (dividing by 100). Finally, equal weights were considered for each ordered aggregation, and equal weights given to each expert. The $V-V$ and $E-V$ matrices obtained from each expert were aggregated using Eqs. (36) and (37), and can be seen in Tables 4 and 5.

In the next stage, an expert in the organization's policies was asked to determine acceptable risk values for each of the variables in Table 6. For example, the related expert was asked:

What percentage do you accept for the risks and changes in personnel medical expenses, according to organizational policies?

The questionnaire used for obtaining acceptable risk values can be found in Appendix 2.

Table 4. The $(E-V)^T$ matrix

	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}	V_{11}	V_{12}	V_{13}
E_1	0	0	0	0	0	**-0.2**	**-0.3**	**-0.5**	0	0	0	0	0
E_2	**-0.2**	0	0	0	0	0	0	0	0	0	0	0	0
E_3	**-0.2**	0	0	**0.5**	0	0	0	0	0	0	0	0	0
E_4	**-0.4**	0	0	**0.2**	0	0	0	0	0	0	0	0	0
E_5	0	**0.25**	**0.39**	0	**0.3**	0	0	0	0	0	0	0	0

Table 5. The $(V-V)^T$ matrix

	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}	V_{11}	V_{12}	V_{13}
V_1	0	0	0	0	0	0	0	0	**0.5**	0	0	0	0
V_2	0	0	0	0	0	0	0	0	**-0.55**	0	0	0	0
V_3	0	0	0	0	0	0	0	0	0	0	**0.2**	0	0
V_4	0	0	0	0	0	0	0	0	0	0	**0.45**	0	0

$\boldsymbol{V_5}$	0	0	0	0	0	0	0	0	**-0.4**	0	0	0	0
$\boldsymbol{V_6}$	0	0	0	0	0	0	0	0	0	0	0	**0.7**	0
$\boldsymbol{V_7}$	0	0	0	0	0	0	0	0	0	0	0	**0.7**	0
$\boldsymbol{V_8}$	0	0	0	0	0	0	0	0	0	0	0	**0.22**	0
$\boldsymbol{V_9}$	0	0	0	0	0	0	0	0	0	**-0.9**	**0**	0	0
$\boldsymbol{V_{10}}$	0	0	0	0	0	0	0	0	0	0	**0.55**	0	0
$\boldsymbol{V_{11}}$	0	0	0	0	0	0	0	0	0	**0**	0	0	**-0.6**
$\boldsymbol{V_{12}}$	0	0	0	0	0	0	0	0	0	0	0	0	**0.9**
$\boldsymbol{V_{13}}$	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 6. The acceptable risk values for each variable

Variable	$\boldsymbol{V_1}$	$\boldsymbol{V_2}$	$\boldsymbol{V_3}$	$\boldsymbol{V_4}$	$\boldsymbol{V_5}$	$\boldsymbol{V_6}$	$\boldsymbol{V_7}$	$\boldsymbol{V_8}$	$\boldsymbol{V_9}$	$\boldsymbol{V_{10}}$	$\boldsymbol{V_{11}}$	$\boldsymbol{V_{12}}$	$\boldsymbol{V_{13}}$
$\boldsymbol{AR}$	0.8	0.8	0.25	0.5	0.8	0.1	0.3	0.3	0.5	0.3	0.5	0.1	0.1

5.2. Determining the risk of each variable in different cases

At this stage, the risk in different situations was calculated, taking into account the potential risk with and without considering the acceptable risk, and while calculating the maximum and minimum risks. A software code based on Algorithm 1 was developed using MATLAB software; the results can be seen in Table 7. For further explanation, the following describes how to obtain the risk values in different cases. For example, the risk of variable V_1 (number of key personnel) is affected by events E_2 (refusal to attend the workplace), E_3 (staff first-degree relative infection) and E_4 (staff infection). Assuming $AR = 0.8$, the calculations are made using Eq. (29) as follows:

$$R(V_1) = (I_{21} + I_{31} + I_{41}) \times (1 - AR_1) = (-0.2 - 0.2 - 0.4) \times (1 - 0.8) = -0.16$$

and without considering AR, we have:

$$R(V_1) = (I_{21} + I_{31} + I_{41}) = (-0.2 - 0.2 - 0.4) = -0.8$$

In addition, the highest and lowest values of V_1 can be calculated using Eq. (31) as follows:

$$\begin{cases} minR(V_1) = -0.16 \\ maxR(V_1) = 0 \end{cases}$$

Table 7. Risk values of each variable in different cases

$\boldsymbol{V_i}$	$\boldsymbol{R(V_i)}$	$\boldsymbol{maxR(V_i)}$	$\boldsymbol{minR(V_i)}$	$\boldsymbol{Without}$ **considering** $\boldsymbol{AR}$
$\boldsymbol{V_1}$	-0.16	0	-0.16	-0.8
$\boldsymbol{V_2}$	0.05	0.05	0	0.25
$\boldsymbol{V_3}$	0.29	0.29	0	0.39
$\boldsymbol{V_4}$	0.35	0.35	0	0.7
$\boldsymbol{V_5}$	0.06	0.06	0	0.3
$\boldsymbol{V_6}$	-0.18	0	-0.18	-0.2

$\boldsymbol{V_7}$	-0.21	0	-0.21	-0.3
$\boldsymbol{V_8}$	-0.35	0	-0.35	-0.5
$\boldsymbol{V_9}$	-0.066	-0.066	0	-0.66
$\boldsymbol{V_{10}}$	0.041	0.041	0	0.59
$\boldsymbol{V_{11}}$	0.12	0.12	0	0.718
$\boldsymbol{V_{12}}$	-0.315	0	-0.315	-0.46
$\boldsymbol{V_{13}}$	-0.32	0	-0.32	-0.845

Now, since the risk results in the "without considering" mode are consistent, the analysis proceeds to the next section in order to carry out the weight calculation and sensitivity analysis.

5.3. Determining the weights of each factor and sensitivity analysis

In this section, in order to prioritize all factors for planning risk management and determining preventive measures, the importance of each factor was determined and ranked using Eq. (33), as shown in Table 8. Also, to investigate problem sensitivity to increases and decreases in the constant value in the risk of various factors, three cases of sensitivity analysis were considered as follows:

Case 1. To determine the risk of each of the variables for each factor, the effect of each of the affecting factors is considered to be 0.1 greater, thus:

$$\forall j = 1, \dots 5, i = 1, \dots ,13, \ \Delta V_{iv} = \Delta V_{jv} = 0.1$$

Case 2. To determine the risk of each of the variables for all factors, the effect of each of the affecting factors is considered to be 0.2 greater, thus:

$$\forall j = 1, \dots 5, i = 1, \dots ,13, \qquad \Delta V_{iv} = \Delta V_{jv} = 0.2$$

Case 3. To determine the risk of each of the variables for all factors, the effect of each affecting factors is considered to be 0.1 lower, thus:

$$\forall j = 1, \dots 5, i = 1, \dots ,13, \ \Delta V_{iv} = \Delta V_{jv} = -0.1$$

The sensitivity analysis values of each of the factors in these three cases are shown with the indices $(S_i|\Delta_1= 0.1)$, $(S_i|\Delta_1= 0.2)$, and $(S_i|\Delta_1= -0.1)$, respectively. The results of the sensitivity analysis are provided in Table 8 and Fig. 9.

Table 8. Ranking and sensitivity analysis results

Factor	**Weight**	**Rank**	$(\boldsymbol{S_i}|\Delta_1= \mathbf{0.1})$	$(\boldsymbol{S_i}|\Delta_1= \mathbf{0.2})$	$(\boldsymbol{S_i}|\Delta_1= \mathbf{-0.1})$
$\boldsymbol{E_1}$	0.3357	1	0.437	0.875	-0.437
$\boldsymbol{E_2}$	0.0078	18	0.0214	0.043	-0.0214
$\boldsymbol{E_3}$	0.0528	7	0.077	0.153	-0.077
$\boldsymbol{E_4}$	0.0337	11	0.077	0.153	-0.077
$\boldsymbol{E_5}$	0.0663	3	0.116	0.231	-0.116
$\boldsymbol{V_1}$	0.0315	12	-0.002	-0.0046	0.002
$\boldsymbol{V_2}$	0.0102	16	0.0007	0.0014	-0.0007

V_3	0.045	9	0.0067	0.0134	-0.0067
V_4	0.063	4	0.008	0.0161	-0.008
V_5	0.011	15	0.0008	0.0017	-0.0008
V_6	0.0514	8	-0.0293	-0.057	0.0293
V_7	0.06	6	-0.0342	-0.068	0.0342
V_8	0.063	4	-0.057	-0.114	0.057
V_9	0.0166	14	-0.005	-0.0104	0.005
V_{10}	0.00787	17	0.0009	0.0019	-0.0009
V_{11}	0.0245	13	0.0107	0.0215	-0.0107
V_{12}	0.076	2	-0.028	-0.0567	0.028
V_{13}	0.0427	10	0	0	0

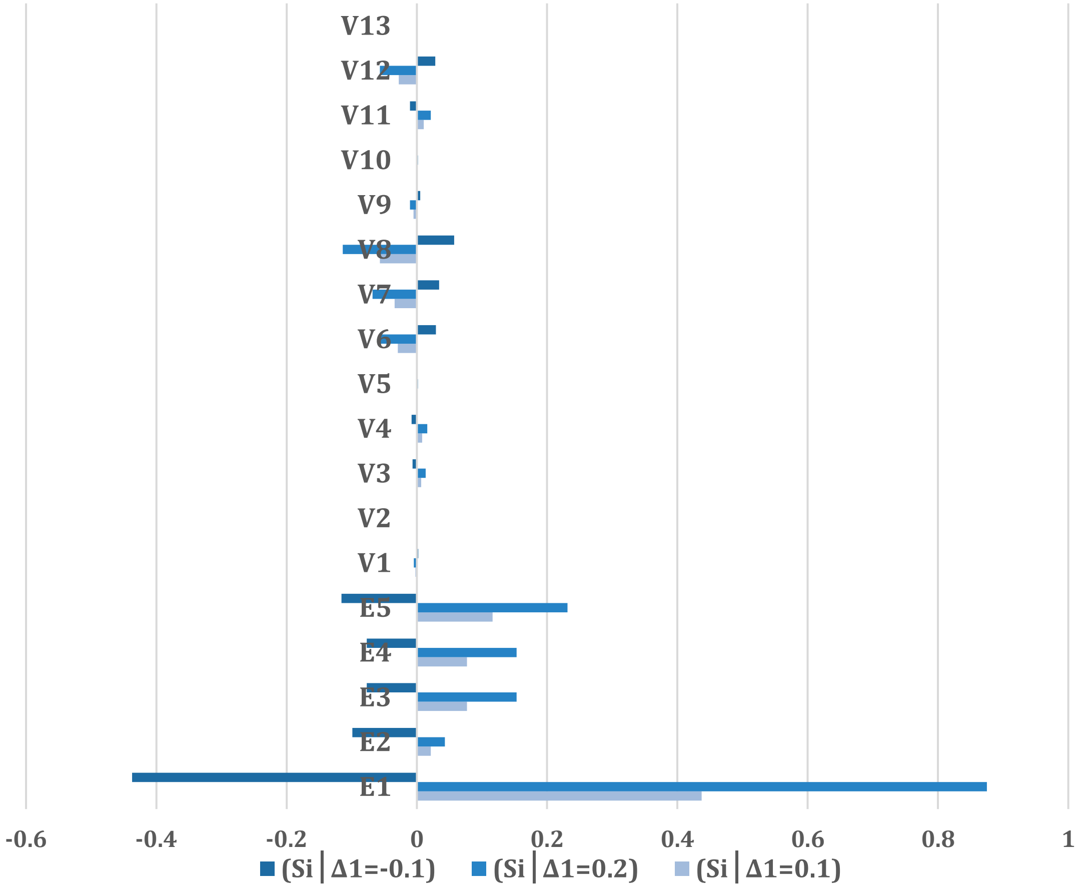


Fig. 9. Sensitivity results

5.4. Robustness analysis

An analytical method's robustness may be defined as an estimation of its capability to remain unaffected by small but deliberate methodological changes across variables [7]. The sensitivity analysis in Section 5.3 showed how much a constant change in values of a factor would change the aggregated risks of all variables. This section investigates to what degree small changes in the most influential factors will have an impact on each specific result. Therefore, the most influential factors should first be identified; as can be seen in Table 8 and Figure 9, the greatest sensitivities are related to factors E_1, E_5, E_3, E_4, and V_8.

Since one of the main outputs of the R.Graph method is the ranking of factors, some dummy values were deliberately entered into each of these factors in order to measure their impacts on the overall ranking of factors. For this purpose, three error levels of 2%, 4%, and 6% were entered into each of the values related to each of the factors. Then the effect of each factor on the results was first examined individually, then the changes entered into a set of influential factors. Overall, 9 separate cases were examined at three error levels, namely, cases $\{E_1\}$, $\{E_3\}$, $\{E_4\}$, $\{E_5\}$, $\{V_8\}$, $\{E_1\}$, $\{E_1, E_5\}$, $\{E_1, E_5, E_3\}$, $\{E_1, E_5, E_3, E_4\}$, and $\{E_1, E_3, E_4, E_5, V_8\}$. This means that each of these sets entered 2%, 4%, and 6% errors in their values, respectively, and the result of the overall ranking of all factors in all these cases was obtained, as can be seen in Tables 9-11. In each of these tables, the ranks that differ from the main case are distinguished in blue. Additionally, to check the closeness of these answers with the answers of the main case, Spearman's correlation coefficient (SCC) [39] was applied, which is a measure of the correlation between the ranking and its values. These SCC results can also be seen in Tables 9-11.

Table 9. The robustness analysis results at 2% error level

Cases	E_1	E_2	E_3	E_4	E_5	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}	V_{11}	V_{12}	V_{13}	**SCC**
	Rank																		
Default case	1	18	7	11	3	12	16	9	4	15	8	6	4	14	17	13	2	10	
E_1	1	17	7	11	4	12	16	9	5	15	8	6	3	14	18	13	2	10	0.913
E_3	1	17	7	11	3	12	16	9	4	15	8	6	5	14	18	13	2	10	0.897
E_4	1	18	7	11	3	12	16	9	5	15	8	6	4	14	17	13	2	10	0.897
E_5	1	18	7	11	3	12	16	9	5	15	8	6	4	14	17	13	2	10	0.897
V_8	1	17	7	11	3	12	16	9	5	15	8	6	4	14	18	13	2	10	0.916
E_1, E_5	1	17	7	11	3	12	16	9	5	15	8	6	4	14	18	13	2	10	0.916
E_1, E_5, E_3	1	17	7	11	3	12	16	9	5	15	8	6	4	14	18	13	2	10	0.916
E_1, E_5, E_3, E_4	1	17	7	11	3	12	16	9	5	15	8	6	4	14	18	13	2	10	0.916
E_1, E_3, E_4, E_5, V_8	1	17	7	11	3	12	16	9	5	15	8	6	4	14	18	13	2	10	0.916

Table 10. The robustness analysis results at 4% error level

Cases	E_1	E_2	E_3	E_4	E_5	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}	V_{11}	V_{12}	V_{13}	**SCC**
	Rank																		
Default case	1	18	7	11	3	12	16	9	4	15	8	6	4	14	17	13	2	10	
E_1	1	17	8	11	4	12	16	9	5	15	7	6	3	14	18	13	2	10	0.91

E_3	1	18	7	11	3	12	16	9	4	15	8	6	5	14	17	13	2	10	0.897
E_4	1	18	7	11	3	12	16	9	5	15	8	6	4	14	17	13	2	10	0.897
E_5	1	18	7	11	3	12	16	9	5	15	8	6	4	14	17	13	2	10	0.897
V_8	1	17	7	11	3	12	16	9	5	15	8	6	4	14	18	13	2	10	0.916
E_1, E_5	1	17	8	11	3	12	16	9	5	15	7	6	4	14	18	13	2	10	0.913
E_1, E_5, E_4	1	17	7	11	3	12	16	9	5	15	8	6	4	14	18	13	2	10	0.916
E_1, E_5, E_3, E_4	1	17	7	11	3	12	16	9	5	15	8	6	4	14	18	13	2	10	0.916
E_1, E_3, E_4, E_5, V_8	1	17	7	11	3	12	16	9	5	15	8	6	4	14	18	13	2	10	0.916

Table 11. The robustness analysis results at 6% error level

Cases	E_1	E_2	E_3	E_4	E_5	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}	V_{11}	V_{12}	V_{13}	SCC
	Rank																		
Default case	1	18	7	11	3	12	16	9	4	15	8	6	4	14	17	13	2	10	
E_1	1	17	8	11	4	12	16	9	6	15	7	5	3	14	18	13	2	10	0.907
E_3	1	18	7	11	3	12	16	9	4	15	8	6	5	14	17	13	2	10	0.897
E_4	1	18	7	11	3	12	16	9	4	15	8	6	5	14	17	13	2	10	0.897
E_5	1	17	7	11	3	12	16	9	5	15	8	6	4	14	18	13	2	10	0.916
V_8	1	17	7	11	4	12	16	9	5	15	8	6	3	14	18	13	2	10	0.9132
E_1, E_5	1	17	8	11	3	12	16	9	6	15	7	5	4	14	18	13	2	10	0.91
E_1, E_5, E_3	1	17	7	11	3	12	16	9	5	15	8	6	4	14	18	13	2	10	0.916
E_1, E_5, E_3, E_4	1	18	7	11	3	12	16	9	5	15	8	6	4	14	17	13	2	10	0.897
E_1, E_3, E_4, E_5, V_8	1	18	7	11	4	12	16	9	5	15	8	6	3	14	17	13	2	10	0.894

5.5. Comparing risk analysis with results observed

As discussed in Section 4, the risk analysis horizon was considered for the case study for a period of one year. However, at the time of writing this article, 6 months have elapsed since the risk analysis was conducted. Thus, Table 12 is provided in order to compare how close the R.Graph risk prediction results obtained were to the changes observed after 6 months, according to available data. Of course, it is worth noting that the values of risk analysis are substantially different from the observed values, due to the existence of the acceptable risk factor. Moreover, using forecasts as inputs in decision-making processes often results in self-predicted outcomes – a problem known as self-negating forecasts, or the prophet dilemma [30]. However, it can be seen that the predicted and observed values in many cases are relatively close.

Table 12. Risk analysis results vs. observed results

V_i	Predicted risk	Observed values
V_1	-0.24	NA
V_2	0.05	0.25
V_3	0.29	0.29
V_4	0.35	0.25

$\boldsymbol{V_5}$	0.06	0.2
$\boldsymbol{V_6}$	-0.18	-0.15
$\boldsymbol{V_7}$	-0.21	-0.2
$\boldsymbol{V_8}$	-0.35	-0.2
$\boldsymbol{V_9}$	-0.086	-0.2
$\boldsymbol{V_{10}}$	0.054	0.2
$\boldsymbol{V_{11}}$	0.123	0.1
$\boldsymbol{V_{12}}$	-0.315	-0.2
$\boldsymbol{V_{13}}$	-0.312	-0.2

NA=Not available

5.6. Discussion

- Risk values for each of the variables, provided in Table 7, indicate how much the value of the variable will change, assuming that all events and variables affecting a variable are considered. Positive values indicate an increase and negative values indicate a decrease. According to Table 7, the amount of risk variable of total profit is calculated at -0.32, which shows that if the previous profit forecast (pre-Coronavirus) was 1000 monetary units, the new forecast (according to Eq. (22) and the calculated risk) would be 1000×(1-0.32) = 680 monetary units, considering the occurrence of the influential factors. It is also possible to see the effect of considering or not considering acceptable risk in Table 7. Many risk values in the real world can be compensated for, which is considered in the R.Graph model as an acceptable factor for the correction of risk values. Also, according to the results of Table 7, it can be seen that the maximum or minimum values of each variable are equal to the risk values of that variable. The main reason for this is when all the factors affecting the risk of that variable have moved in the same direction, or when all of them have increased the risk of the desired variable, or when all of them have been used to reduce the risk of that variable.

- Table 8 shows the importance of each factor on the total risks of problem variables, and also their ranking. It can be seen that the Coronavirus pandemic is the most important of all the factors that could have already been predicted, because all the values of the risks were due to its occurrence. It is also observed that the highest importance among the variables is related to the power branch sales revenue, and the lowest concern belongs to the variable of degree of work difficulty. Decision-makers and managers in the organization can thus design and implement preventive plans according to the importance of each individual factor, in order to reduce its risk and its consequences.

- According to Table 8, the effect of increasing or decreasing the values of each factor on the risk of its children can be examined, which is termed the amount of sensitivity analysis of that factor. It can be observed that the highest sensitivities to changing values are seen in power branch sales revenue in variables. Moreover, it is also observed that the problem is very sensitive to changes in the new safety regulations, in addition to the Coronavirus pandemic. It can also be seen that, for each factor, the following is apparent:

$$(S_i|\Delta_1 = 0.1) = -(S_i|\Delta_1 = -0.1)$$

Generally, it can be said that the problem sensitivity to increases or decreases in a certain value are opposites in the R.Graph method, thus:

$$\begin{cases} S^{vi}\middle|\Delta V_{iv} = -S^{vi}\middle| - \Delta V_{iv} \\ S^{ej}\middle|\Delta V_{jv} = -S^{ej}\middle| - \Delta V_{jv} \end{cases}$$

- To investigate the degree to which the model ranking results are robust subject to minor changes, three different scenarios of change in the values of the influencing factors were carried out. The results are presented in Tables 9 to 11; it can be seen that the Spearman's correlation coefficient values changed from 0.898 to 0.916 in worst and best cases. This indicates slight changes in the ranking results, and an acceptable degree of robustness within the model.

- The R.Graph method was developed to provide a framework for risk analysis based on the degree of predicted changes in the variables of interest to an organization, taking into account managerial factors, such as acceptable risk factors. Although the main purpose of this method is not to determine preventive actions, it can be a useful tool for ranking various factors, allowing for appropriate planning to implement preventive measures. It permits decision-makers to effectively determine policies and interventions affecting system outputs, and to examine their impact on reducing adverse effects or increasing desired outcomes. In the present case study, some recommendations of the R.Graph method to reduce possible risks in the variables are as follows:

    1) Teleworking and staff turnover: these may reduce effects on “*Number of key personnel”*, *“Environmental health costs”, “Total personnel efficiency*”, *“Personnel medical expenses”*, *“Level of stress”, “Total cost”, “Project delay rate”* and *“Total profit”.*
    2) Reducing hours of physical presence: these may reduce effects on “*Number of key personnel”, “Personnel medical expenses”, “Total personnel efficiency*”, *“Level of stress”, “Project delay rate”, “Total cost”* and *“Total profit”.*
    3) Periodic Corona tests: for reducing the effects on “*Number of key personnel”, “Personnel medical expenses”, “Level of stress”, “Total personnel efficiency*”, “*Project delay rate” , Total cost”* and *“Total profit”.*
    4) Increasing environmental health measures: these may reduce effects on “*Number of key personnel”, “Personnel medical expenses”, “Level of stress”, “Total personnel efficiency*”, “*Project delay rate” , Total cost”* and *“Total profit”.*
    5) Increasing project duration (time revision): these may reduce effects on*“Project delay rate”.*

6) Allocating special financial packages for companies affiliated to the Ministry of Energy (for example, using National Development Fund resources): for reducing the effects on “*Percentage of receivables*”, “*Energy sales revenue*”, “*Power branch sales revenue*”, *Total income”* and *“Total profit”.*
7) Involving other employees, or employing external contract staff: for reducing the effects on “*Number of key personnel”, “Total personnel efficiency*”, “*Project delay rate”, Total cost”* and *“Total profit”.*
8) Specialist health and medical support for personnel: these may reduce effects on *“Total personnel efficiency*”, “*Project delay rate”*, *Total cost”* and *“Total profit”.*

- For many problems, modeling with traditional techniques is difficult or even impossible. This is especially true when certain statistical data related to the model and its parameters are not available, and/or it is difficult to extract the relationships between the components of the modeled system from the quantitative prediction models such as time series models. In such cases, opinions provided by knowledgeable individuals are the best available data. The R.Graph method can be seen as a tool for modeling and simulating systems, using data obtained from experts in the field, thus providing an appropriate, interpretable framework for decision-makers and system modelers. In this method, the intended data can be collected and aggregated through interviews, workshops, or surveys, or by using the Delphi method and questionnaire, or a combination of these methods. Additionally, experts can be asked to vote on entries anonymously using an online questionnaire, then to discuss the results directly.
- In the proposed R.Graph method, information about indirect interactions between system components is extracted based on direct interactions. Indeed, direct interactions are input data, and the model’s utility lies in analyzing indirect interactions. This is especially useful, since, in a complex network with a variety of factors, incidental interactions and their causal chains can be complicated and lengthy. Additionally, the proposed R.Graph method can identify the importance of a system component that may not appear to be related to another element, such as when some seemingly essential components may be canceled or neutralized by network interactions.
- In the R.Graph method, the risk of each variable was considered in terms of the linear sum of changes in the influential variables, as well as in terms of influential events which may affect a variable independently. In this method, events can also be considered as categorical variables. In addition, the mutual effect of each event, and the amount of changes were considered to be definite. Definite consideration of the occurrence of events and their impact is based on the assumption that it is known that the event in question will occur sooner or later; the purpose is to determine its impact. Alternatively, it may be desirable to estimate the change in a variable if it occurs. Another

possible assumption may be that the uncertainty regarding the specific event is so high, or the available information is so low, that it is impossible to determine the probability of the event.

- Generally speaking, interpretability of an algorithm refers to how causes and effects may be observed within a system, allowing for a ability to predict outcomes [33]. Explicability, on the other hand, refers to how the internal mechanics of a model can be expressed in simpler human terminology [33]. Algorithms based on the concept of causality, such as the proposed R.Graph method, have the ability to be easily interpreted, and the results can be explained to decision-makers. Therefore, its results are more reliable for managers and decision-makers, as they can participate in all stages of analysis.
- The R.Graph method is logically different from other existing methods such as Bayesian networks and CIAMs, which use discrete and possible events to estimate the event probabilities. The most important differences between R.Graph and other causal methods can be seen in: the difference of system inputs (considering change instead of scenario); the difference of interactions between factors (how to consider the relationships between factors); assuming a definite nature instead of a probabilistic one; the display of various factors; and considering a static nature. Indeed, the proposed R.Graph risk concept was developed assuming possible variations in model variables, so that it can be used in cases where the decision-maker is interested in investigating the effect of different events on a series of specific variables, or is interested in examining the rate of effect due to unforeseen events. Other advantages of the R.Graph method include: considering acceptable risk levels for desired organizational parameters; determining the highest and lowest risk values of each variable; determining the weight and ranking of factors; and presenting an appropriate method for model sensitivity analysis. A selection of causal models have been compared with the proposed R.Graph from different perspectives, and the findings are depicted in Table 13.

Table 13. Comparison of causal models from different perspectives

Method	**Input**		**Nature**					
	Event	**Variable**	**Deterministic**	**Probabilistic**	**Static**	**Dynamic**	**Discrete**	**Continuous**
MICMAC [5]	✓	✓	✓		✓		✓	
EXIT [27]	✓		✓		✓		✓	
DEMATEL [46]	✓	✓	✓		✓		✓	
Cognitive maps [25]	✓	✓	✓		✓		✓	
Structural equation modeling [2]	✓	✓	✓		✓			✓
Bayesian networks [10]	✓			✓	✓		✓	✓
Dynamic Bayesian networks [9]	✓			✓		✓	✓	✓
BASICS [17]	✓			✓	✓		✓	
AXIOM [29]	✓			✓	✓	✓	✓	
Fault tree [19]	✓			✓	✓		✓	
Event tree [32]	✓			✓	✓		✓	

Petri nets [47]	✓	✓		✓		✓	✓	
Proposed R.Graph	✓	✓	✓		✓			✓

6. Conclusion

Risks and disruptions, especially unforeseen ones, have led many companies today to be concerned about the consequences on the complex, global business environment. The Coronavirus pandemic represents such a specific disruptive case. Epidemic/pandemic outbreaks lead to long-term disruptions, which are unpredictable in terms of time, severity, and scale. Even with certain known, low-probability, high-impact events, many traditional risk analysis methods have proven insufficient in assessing their risks and outcomes.

The present paper presented a new risk analysis method to measure the risk of interactive factors in the causal chain which can be fully explainable for decision-makers. Its application was studied in a risk analysis of Coronavirus on the Iranian electricity industry. The advantages of the proposed model included: determining the amount of change in variables; accounting for preferred organizational parameters, such as acceptable risk; determining the importance and ranking of factors; analyzing sensitivity; and interpretability and explicability for decision-makers.

Simplified assumptions were made in the development of the R.Graph method in order to better comprehend this new model and its applicability. Consequently, new assumptions can be introduced as future research topics developing upon the current study. For instance, the R.Graph model has been developed assuming that the problem in hand is definite, so its extension into a probabilistic model to capture randomness can provide useful future research. Moreover, linearity is one of the main assumptions in the R.Graph method, but the linearity assumption is not always established in certain risk analysis problems. It is also suggested to employ supervised [15] or unsupervised [6] learning methods in cases where sufficient data is available for statistical interpretation. Another issue not discussed in the R.Graph method is how to combine the information obtained from experts with methods to consider the reliability of their evaluations [43]; this can be considered as another future research area. Finally, other areas of research might pursue the development of the R.Graph model in a dynamic mode [20], while considering other uncertainties [34] in input data.

Appendix 1. Questionnaire A

Dear respondents,

The COVID-19 epidemic in Iran is part of the worldwide_Coronavirus pandemic, which has had various consequences, including social and economic implications, for the entire country. One of the most critical parts of Iran's economy that has been significantly affected by the Coronavirus is the electricity industry. COVID-19 is projected to reduce production volumes and shut down manufacturing, contracting, and consulting units, leaving manufacturing units temporarily closed and costing a large number of jobs. The volume of executive activities will be reduced, and ongoing projects may also be delayed; with the disruption of trade, imports and exports related to the electricity industry will additionally be severely disrupted. The power grid is unstable, and blackouts occur. Delays in the private sector, due to declining production, will lead to the closure and bankruptcy of manufacturers and contractors in the electricity industry, and ultimately the electricity industry economy will suffer direct and indirect losses due to delays in bank payments, social security, and taxes.

The purpose of this questionnaire is to evaluate the impact of COVID-19 on the intended variables in the electricity industry. We would be grateful if you would respond to the questions in Section I, and fill the response sheet in Section II. All personal information will remain fully confidential, and will not be shared with anyone.

Sincerely,
Authors

Section I

General expert information

Please select only one option

1. What is your highest qualification level?

- Graduate
- Postgraduate
- Doctorate
- Other: please specify …………

2. How long is your related work experience?

- Less than 10 years
- 10–15 years
- 15–20 years
- Greater than 20 years

3. What is your area of expertise related to the electricity industry? Please specify ....

4. Who is the designated decision-maker(s) in your particular organization?

- Manager
- Supervisor
- Chief executive officer
- R&D team member
- Other: please specify..........

Section II

Determining the amount of risk of each factor

The purpose of this questionnaire is to evaluate the impact of COVID-19 on specific variables in the electricity industry, which is determined by the percentage of variability (percentage decrease or percentage increase), and the risk of that variable.

Note:

Note that if a factor or change in one variable causes a positive change in another variable, please indicate it with a positive sign, and use a negative sign if it leads to a decrease. For example**:**

How many percentage points do you think new safety regulations will alter job difficulty?

Your comment: + 50% ,which means that you think it would increase by 50%.

Therefore, you are asked to determine the effect of COVID-19 on each of these factors, according to the instructions mentioned.

Question	**The evaluation**
How many percentage points do you think new safety regulations will alter job difficulty?	
How many percentage points do you think new safety regulations will alter environmental health costs?	
How many percentage points do you think new safety regulations will alter levels of stress?	
How many percentage points do you think staff infections will alter number of key personnel?	
How many percentage points do you think staff infections will alter personnel medical expenses?	
How many percentage points do you think first-degree relatives being infected will alter number of key personnel?	
How many percentage points do you think first-degree relatives being infected will alter personnel medical expenses?	
How many percentage points do you think the coronavirus pandemic will alter the percentage of receivables?	
How many percentage points do you think the coronavirus pandemic will alter energy sales revenue?	
How many percentage points do you think the coronavirus pandemic will alter power branch sales revenue?	
How many percentage points do you think a one hundred percent increase in personnel medical expenses will alter total cost?	
How many percentage points do you think a one hundred percent increase in environmental health costs will alter total cost?	
How many percentage points do you think a one hundred percent increase in job difficulty will alter total personnel efficiency?	

How many percentage points do you think a one hundred percent increase in levels of stress will alter job total personnel efficiency?
How many percentage points do you think a one hundred percent increase in number of key personnel will alter total personnel efficiency?
How many percentage points do you think a one hundred percent increase in total personnel efficiency will alter project delay rate?
How many percentage points do you think a one hundred percent increase in project delay rate will alter total income?
How many percentage points do you think a one hundred percent increase in percentage of receivables will alter total income?
How many percentage points do you think a one hundred percent increase in energy sales revenue will alter total income?
How many percentage points do you think a one hundred percent increase in power branch sales revenue will alter total income?
How many percentage points do you think a one hundred percent increase in total cost will alter total profit?
How many percentage points do you think a one hundred percent increase in total income will alter total profit?

Name of expert ……………………….
Authority …………………………………
Department ………………………………..
Email………………………………………..
Date and place……………………………...

Appendix 2. Questionnaire B

Dear respondents

Greetings.

The COVID-19 epidemic in Iran is part of the worldwide Coronavirus pandemic, which has had various consequences, including social and economic implications, for the entire country. One of the most critical parts of Iran's economy that has been significantly affected by the Coronavirus is the electricity industry. COVID-19 is projected to reduce production volumes and shut down manufacturing, contracting, and consulting units, leaving manufacturing units temporarily closed and costing a large number of jobs. The volume of executive activities will be reduced, and ongoing projects may also be delayed; with the disruption of trade, imports and exports related to the electricity industry will additionally be severely disrupted. The power grid is unstable, and blackouts occur. Delays in the private sector, due to declining production, will lead to the closure and bankruptcy of manufacturers and contractors in the electricity industry, and ultimately the electricity industry economy will suffer direct and indirect losses due to delays in bank payments, social security, and taxes.

The purpose of this questionnaire is to evaluate the impact of COVID-19 on the intended variables in the electricity industry. We would be grateful if you would respond to the questions in Section

I, and fill the response sheet in Section II. All personal information will remain fully confidential, and will not be shared with anyone.

Sincerely,
Authors

Section I

General expert information

Please select only one option

1. What is your highest qualification level?

- Graduate
- Postgraduate
- Doctorate
- Other: please specify …………

2. How long is your related work experience?

- Less than 10 years
- 10–15 years
- 15–20 years
- Greater than 20 years

3. What is your area of expertise related to the electricity industry? Please specify ....

4. Who is the designated decision-maker(s) in your particular organization?

- Manager
- Supervisor
- Chief executive officer
- R&D team member
- Other: please specify..........

Section II

Determining the amount of acceptable risk

The purpose of this section is to determine the risk acceptance of each influence and influential factor in the electricity industry.

Note:

The acceptable levels of risk and changes in a specific variable means the percentage change due to the occurrence or change in the desired variable which can be accepted and/or compensated by the relevant organization and thus not included in their calculations. This denotes the degree of risk acceptable to the organization, which can be expressed as a percentage between 0 and 100. We need your judgment to define the acceptable risk for each variable, so please fill out the following table, based on your organizational policy, using values between 0 and 100.

Phrase	**Your evaluation**
What percentage do you accept for the risks and changes in number of key personnel, according to organizational policies?	
What percentage do you accept for the risks and changes in degree of work difficulty, according to organizational policies?	
What percentage do you accept for the risks and changes in environmental health costs, according to organizational policies?	
What percentage do you accept for the risks and changes in personnel medical expenses, according to organizational policies?	
What percentage do you accept for the risks and changes in level of stress, according to organizational policies?	
What percentage do you accept for the risks and changes in percentage of receivables, according to organizational policies?	
What percentage do you accept for the risks and changes in energy sales revenue, according to organizational policies?	
What percentage do you accept for the risks and changes in power branch sales revenue, according to organizational policies?	
What percentage do you accept for the risks and changes in total personnel efficiency, according to organizational policies?	
What percentage do you accept for the risks and changes in project delay rate, according to organizational policies?	
What percentage do you accept for the risks and changes in total cost, according to organizational policies?	
What percentage do you accept for the risks and changes in total income expenses, according to organizational policies?	
What percentage do you accept for the risks and changes in total profit expenses, according to organizational policies?	

Name of expert ……………………….
Authority …………………………………
Department ………………………………..
Email……………………………………..
Date and place……………………………...

Thank you very much for your valued responses.

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