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Fuzzy Ontological Model of Monitoring and Management of Educational Institution Complex Risks

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Abstract

A general education institution faces various types of external and internal environment risks that affect the achievement of the main goals - development and quality of education. The effectiveness of a general education institution in modern conditions is associated with implementation of complex risk management in the process of its functioning and development. In this article, an ontological model is constructed that reflects all terms of the field of complex risk management in an educational institution and the links between them. It also describes a method for introducing fuzziness into an ontological model. A fragment of the ontological model for monitoring and managing complex risks of an educational institution is given. The article considers a method of constructing the suggested fuzzy ontological model, ready for further use for monitoring and managing complex risks, and gives an example of using such a model for ranking risk sources.

Keywords: educational institution, complex risk monitoring and management, fuzzy ontological model, method of constructing, professional standard, professional competences

INTRODUCTION

The peculiarity of a general education institution management in modern conditions consists in the activity of the administration to achieve the goals determined by the transition of school to a state of development and conformity of the educational program implementation results with the requirements of the Federal State Educational Standard. In this regard, the tasks of monitoring and managing risks of the internal environment of an educational institution are becoming quite relevant, since they are related to the infrastructure, the technologies being implemented, the qualifications of the administrative staff, the level of teachers' professional and pedagogical competencies, etc.

Teaching staff is the main resource in solving the task of developing a general education institution and achieving educational results by students, and therefore they must have a high level of professional competence. The introduction of the professional standard for teachers brought about the need to monitor the compliance of the professional standard requirements and the actual level of professional competence of teachers in a school, as well as to assess their professional activities. It should be noted that the use of innovative expert and analytical technologies that allow not only to solve the problem of developing professional and pedagogical competencies based on a multifunctional approach within the framework of a specially organized activity, but also to assess them, entails certain risks [1].

Analysis of such risks shows that they are not just individual events that have a source and consequences, but they can also be built into chains, linked by cause-effect, chronological or other types of relations.

On the other hand, a review of models [2-5] applicable to risk management showed that the most flexible model for constructing arbitrary relationships and dependencies is the ontology model.

ONTOLOGICAL MODEL OF COMPLEX RISK MONITORING AND MANAGEMENT

The ontological model is formally defined as follows [6, 7]:

$$O = \langle C, R, F \rangle`,$$

where C is a finite set of concepts of the subject field defined by the ontology O; R is a finite set of relations between concepts of the subject field; F is a finite set of interpretation functions (axiomatization) defined in the concepts and/or relations of the ontology O.

This ontological model does not meet all the requirements for model support for monitoring and managing complex risks. It does not take into account completeness of information about a complex risk. This description of ontology, for example, lacks attributes of the model concepts and a description of the uncertainty of the relations between the model concepts. To solve the task of monitoring and managing complex risks, an extended description of the ontology model is required, that will meet all the requirements.

For this a fuzzy ontological model FO is suggested in the following form [8]:

$$FO = \langle C, A, R, F \rangle ,$$

where C is a finite set of concepts of the subject field defined by the ontology FO; A is finite set of concept attributes; R is a finite set of fuzzy relations between the subject field concepts; F is a finite set of axioms defined in concepts and/or relations of the ontology FO.

Using consequences of implementing complex risks as input and reasons for implementing risk as output suggests including the following layers in the model:

1. risk source layer;
2. undesirable event layer;
3. layer of undesirable event implementation consequences;
4. layer of risk management activities;
5. layer of economic activity indicators that reflect the occurrence of risks;
6. risk indicators layer;
7. layer of activities aimed at eliminating sources of risk.

The fuzzy ontological model contains three types of relations:

– hierarchical relations;
– relations of type "causes";
– relations of type "affects".

Relations of the hierarchical type describe a certain hierarchical structure. Typically, this type of relation is used to describe indicators related to risks (risk indicators and economic performance indicators that reflect the occurrence of risks).

Relations of the type "Causes" suggest some causal relation between the elements of the model. This relation can also be described by an assessment of the possibility of calling one model element by another.

Relations of the type "Affects" imply an assessment of the degree of impact of one model element on another. Such relations, as a rule, bear a level of consequences or a level of reduction of consequences.

Figure 1 presents the structure of a fuzzy ontological model for solving problems of monitoring and managing complex risks.

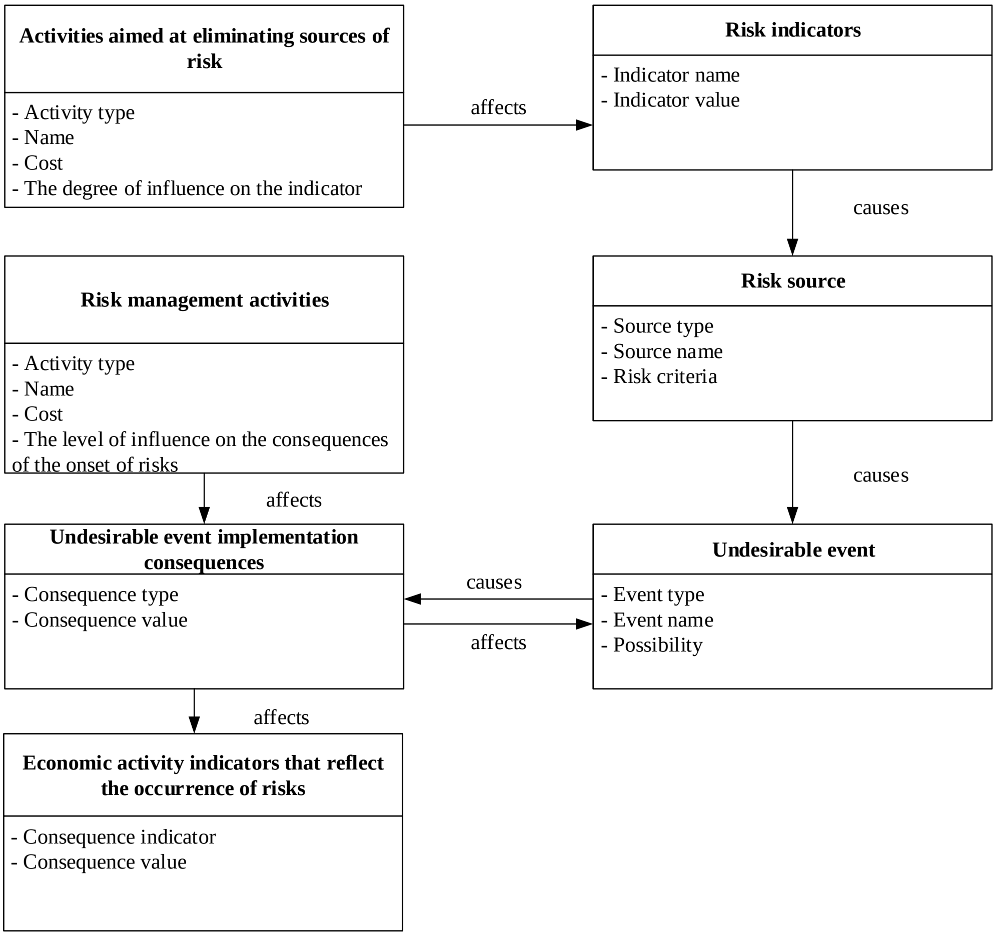

Figure 1: Example of relations of the type "causes"

The model should be based on a fuzzy approach, since most of the staff assessments related to the implementation of risks are qualitative and risk management is carried out in the context of uncertainty of the relations between concepts [8]. As a tool for introducing fuzziness, weights w_{ij} between the concepts of the model for relations of the type "causes" are used. The weights w_{ij} are defined by the fuzzy variables $\langle W_i, D_{w_i}, \tilde{C}_{w_i} \rangle$, where $i \in I = \{1, 2...r\}$, r is the number of relations between the model concepts, D_{w_i} is the base set of the fuzzy variable, $\tilde{C}_{w_i}$ is a fuzzy set in the base set D_{w_i} describing this variable.

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The fuzzy set membership function of a fuzzy variable can be defined using the Gaussian function. Thus, fuzzy relations of the type "causes" will be described by a pair of numbers [*x1*, *x2*], where *x1* is the concentration coefficient of the membership function, and *x2* is the coordinate of the membership function maximum.

Figure 2 shows a fragment of the fuzzy ontological model for monitoring and managing an educational institution risks in development of professional and pedagogical competencies of teachers.

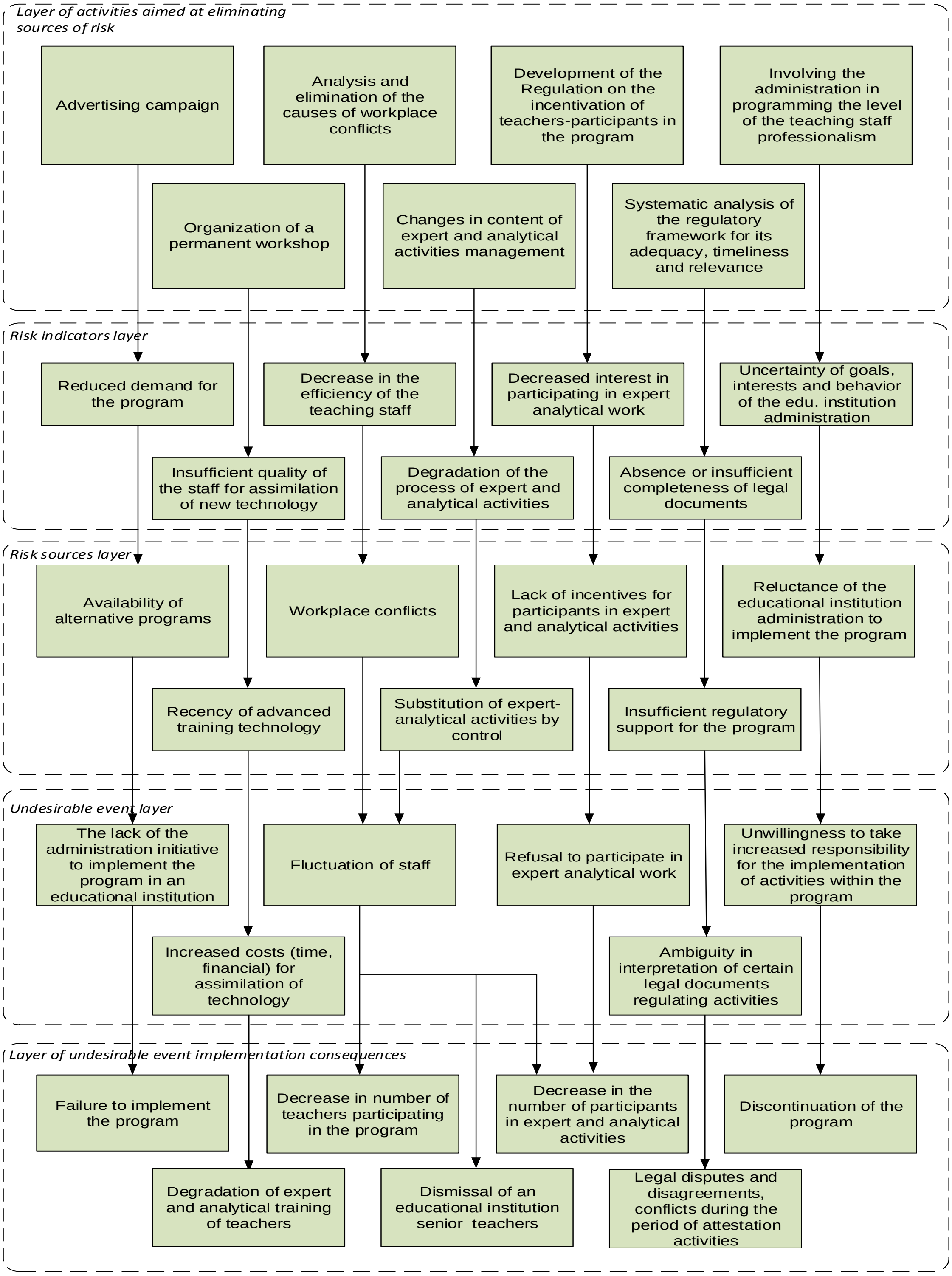

Figure 2: fragment of the fuzzy ontological model for monitoring and managing educational institution complex risks in development of professional and pedagogical competencies of teachers

THE METHOD OF CONSTRUCTING THE MODEL

Stage 1. Analysis of the peculiarities and conditions of the functioning of an educational institution, for which a task of managing complex risks in development of professional and pedagogical competences of teachers is being solved.

At this stage, the model developer must determine the key requirements associated with the boundaries of the modeled subject and the degree of detail in the selection of concepts, taking into account the context of the ontological model development. In other words, the requirements are determined for solving the task of managing the risks of an educational institution activities in development of professional and pedagogical competences of teachers.

This stage also includes analysis of the peculiarities of functioning of an educational institution, analysis of external influence, the identification of specific features of structural units activities, services and the teaching staff as a whole.

Implementation of this stage is based on the study of legal documents and special literature related to the activities of an educational institution [9]. In case of insufficient level of activity documentation completeness even at early stages of constructing an ontological model, it is possible to involve experts with extensive experience and knowledge in solving the task of managing complex risks in the activity of an educational institution for development of professional and pedagogical competences of teachers.

Stage 2. Selection of the basic concepts of the subject: is a set of concepts.

While forming basic concepts, it is recommended to mark out the main terms of the subject from different documents, preserving the information about the source document. This is necessary to simplify the work at the stage of distributing concepts over semantic layers, as well as building links from concepts to documents.

Stage 3. Determining the height of the "ontology tree" (semantic layers of the model).

A layer reflects the structure of concepts associated with a particular direction of research or a specific task. Due to the multi-layered organization of the ontological model, even complex ontologies are easily readable and clear for a user.

Stage 4. Distributing concepts over model layers.

Step 1. Identification of concepts related to the layer "Risk indicators".

Step 2. Identification of concepts related to the layer "Risk sources".

Step 3. Identification of concepts related to the layer "Undesirable events".

Step 4. Identification of concepts related to the layer "Risk implementation consequences".

Step 5. Identification of concepts related to the layer "Economic activity indicators that reflect the occurrence of risks".

Step 6. Identification of concepts related to the layer "Activities aimed at elimination or reduction of risk consequences".

Step 7. Identification of concepts related to the layer "Activities aimed at eliminating sources of risk".

When performing this stage, one should be guided by the belonging of concepts to source documents that are definitely associated with one or another layer of ontology.

Stage 5. Describing concept attributes: is a set of the i-th attribute concepts.

Each attribute has, at least, a name and a value (or its analog) and is used to store object-specific information that is attached to it.

Stage 6. Forming concept instances.

Instances are base components of ontology.

Stage 7. Defining relations between concepts: is a set of relations.

Step 1. Defining hierarchic relations.

For each concept a superclass and subclasses should be searched for. Perhaps, in this way, new concepts will be revealed (after consulting with experts, one must either reject the identified concepts or introduce them into the model). The first step yields several (at least one) hierarchies. That means, there may be several non-related subsets of concepts [10].

Step 2. Defining relations of the type "causes".

This type of relations reflects the possibility of occurrence of the "caused" model concept in case of occurrence of the "causing" concept.

Step 3. Defining relations of the type "affects".

This type of relationship reflects the influence of one concept on another.

At this stage, relations of all types are constructed without assigning weights to fuzzy relations.

Stage 8. Fuzzification of the model.

As a fuzzification tool weights between model concepts for relations of the type "causes" are used. The weights are defined by fuzzy variables $\left\langle W_i, D_{W_i}, \tilde{C}_{W_i} \right\rangle$, where $i \in I = \{1, 2...r\}$, r is the number of relations between model concepts, D_{W_i} is the base set of the fuzzy variable, $\tilde{C}_{W_i}$ is a fuzzy set at the base set D_{W_i}, describing this variable.

Construction of the model is based on consultations with subject experts, the study of special literature and official documents related to the activities of the university branch.

THE RISK ASSESSMENT METHOD USING A FUZZY ONTOLOGICAL MODEL

The risk occurrence monitoring method using an ontological model for monitoring and managing complex risks includes the following steps:

Stage 1. Specifying educational institution activity indicators reflecting the risks as input of the model.

Since the implemented risk is complex, the user can specify several heterogeneous indicators as inputs.

Stage 2. The analysis of fuzzy relations of the type "affects" and "causes" between the concepts of the model for searching for risk implementation sources.

Step 1. Determination of all relations between the given performance indicators for the development of teachers' professional and pedagogical competencies and the consequences of implementing undesirable events.

At this step, a list of fuzzy relations is formed, linking selected indicators and consequences, the source of which is the consequences layer of the fuzzy ontological model.

The list of fuzzy relations includes names of consequences the indicators are associated to and the fuzzy variable , which is the weight of the identified fuzzy relation.

Step 2. Determination of all relations between the consequences revealed at the previous step and undesired events.

At this step, a list of fuzzy relations is formed that links the consequences and undesirable events that are selected from the undesirable events layer of the fuzzy ontological model.

The list of fuzzy relations includes names of undesirable events which the consequences revealed at the previous step are associated to and the fuzzy variable , which is the weight of the corresponding fuzzy relation.

Step 3. Determination of all relations between the undesired events found at the previous step and sources of risks.

At this step, a list of fuzzy relations is formed that links undesirable events and sources of risks that are selected from the risk source layer of the fuzzy ontological model.

The list of fuzzy relations includes names of the risk sources the undesirable events found at the previous step are associated to and the fuzzy variable W_i , which is the weight of the corresponding fuzzy relation.

Stage 3. Accumulation of all fuzzy relations between the given indicators and each source of complex risks identified at the previous stage [11].

The given indicators of the educational institution activity for the development of the teachers' professional and pedagogical competences, reflecting the occurrence of risks and each found source of their occurrence, are connected by several fuzzy relations, at least by three (it should be borne in mind that there may be several links of the type "undesirable event" - "consequence"). The fuzzy set membership function D_{W_i} of the fuzzy variable w_i will be defined using the Gaussian function. Therefore fuzzy relations of the type "causes" will be described by a pair of numbers [*x1, x2*], where x1 is the concentration coefficient of the membership function, and *x2* is the coordinate of the membership function maximum.

If all the fuzzy sets $\tilde{C}_{W_i}$, corresponding to fuzzy relations linking the given risk implementation consequences and each found cause of complex risk implementation, have a product space then the accumulation of all fuzzy relations is calculated using the min-conjunction operation.

$$\mu_{\tilde{C}^*=\tilde{C}_1^*\wedge\tilde{C}_2^*...\wedge\tilde{C}_m^*}(d)=\min\{\mu_{\tilde{C}_1}(d),\mu_{\tilde{C}_2}(d),...,\mu_{\tilde{C}_m}(d)\},\forall d\in D,$$

where *m* is the number of considered fuzzy relations;

$\tilde{C}_1, \tilde{C}_{2,}, ..., \tilde{C}_m$ are fuzzy sets defining certain fuzzy relations;

$\tilde{C}^* = \tilde{C}_1^* \wedge \tilde{C}_2^* ... \wedge \tilde{C}_m^*$ is the resultant accumulated fuzzy set defined at *D*.

If all the fuzzy sets $\tilde{C}_{W_i}$, corresponding to fuzzy relations, do not have a product space, the accumulation result will be the left-most fuzzy set at the base set *D*. That means, the smallest fuzzy variable $\left\langle W_i, D_{W_i}, \tilde{C}_{W_i} \right\rangle$ remains in the analysis.

Stage 4. Defuzzification of the accumulated priority values of each potential source of risk with the "center of gravity" method [12].

For this method the unfuzzy value y' of the output variable is calculated as the center of gravity of the membership function $\mu_{\beta'}(y)$ as follows:

$$y' = \frac{\int_{Y_{min}}^{Y_{max}} y\mu_{\beta'}(y)dy}{\int_{Y_{min}}^{Y_{max}} \mu_{\beta'}(y)dy},$$

where $Y_{\min}, Y_{\max}$ are the boundaries of the output variable y fuzzy set carrier interval.

If at the previous stage the fuzzy sets did not have a product space and the left-most fuzzy set at the base set *D* was selected, then the defuzzification is performed using the method of the membership function maximum. The unfuzzy value of the output variable y' is calculated as follows:

$$y' = \arg\sup_y \mu_B(y).$$

Thus, at this stage, for each found source of complex risks implementation, its priority is determined in the form of an unfuzzy value.

Stage 5. Forming at the output of the model a ranked list of potential sources of risk, which caused the implementation of complex risk.

At this stage, potential sources of risk are given in the descending order of their priorities, that is, from the most likely sources to the least likely.

AN EXAMPLE

As an illustration, let us consider the assessment of the impact of workplace conflicts and the substitution of expert-analytical activities by control and dismissals of senior teachers of an educational institution (figure 3).

The figure also reflects fuzzy relations that link indicators to each other. Workplace conflict impact on staff fluctuation is assessed as "moderate", and impact of "Substitution of expert-analytical activities by control" is assessed as "below moderate". In its turn, impact of "Staff fluctuation" on "Dismissal of an educational institution senior teachers" is assessed as "below moderate". Let us perform a ranking of risk sources on the basis of the impact on dismissal of senior teachers.

The first column of figure 4 shows the following relations: impacts of staff fluctuation on dismissal of senior teachers; impacts of workplace conflicts on staff fluctuation. To assess indirect impact of workplace conflicts on the dismissal of senior teachers, we use the aggregation operation (min function). For defuzzification of the obtained value the center of mass method will be used. Thereby, workplace conflicts affect dismissal of senior specialists with an assessment of 0.365.

Similarly, the right column shows the following relations: impacts of staff fluctuation on dismissal of senior teachers of an educational institution; impacts of the substitution of expert-analytical activity by control on staff fluctuation. In order to obtain a comparative assessment of the impact of substitution of expert and analytical activities by control on dismissal of senior specialists, we will also use the min and center of mass methods. The result impact assessment is 0.323. From this perspective, workplace conflicts have a greater impact on dismissal of senior specialists, compared with the substitution of expert-analytical activities by control.

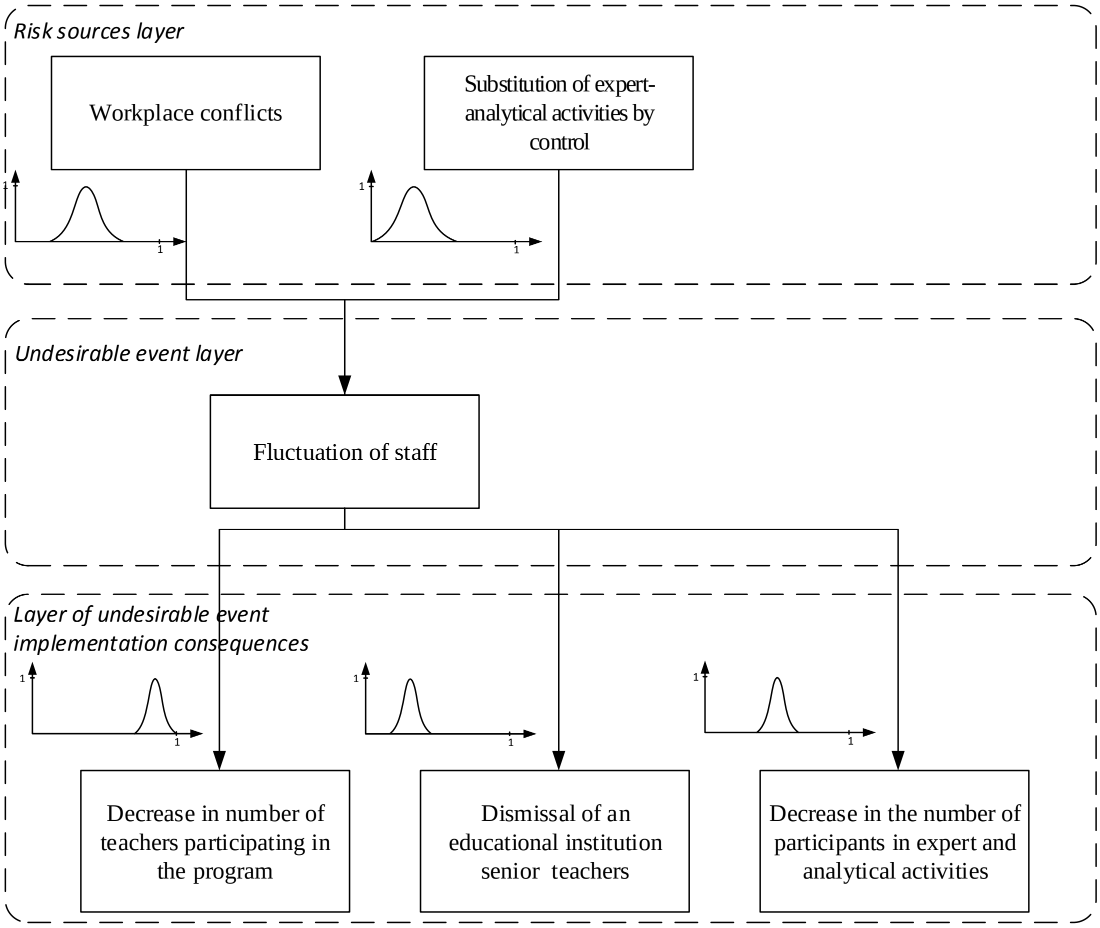

Figure 3: fragment of the fuzzy ontological model for ranking the impact of risk sources on dismissal of educational institution senior teachers

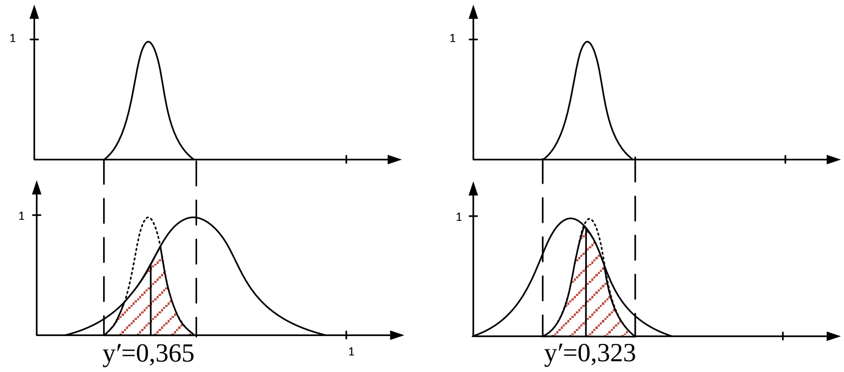

Figure 4: Aggregation of fuzzy values within an ontological mode

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DISCUSSION

Similarly, within the framework of a fuzzy ontological model, the impacts of concepts connected by chains of arbitrary length may be assessed. These assessments can be used to assess the most possible undesirable events and their most characteristic consequences, to identify the most significant sources of risks as well as to identify the most significant activities in terms of risk management.

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