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Intelligent Risk Analysis of Investment Projects in the Extractive Industry

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Abstract: This study introduces an advanced technology for risk analysis in investment projects within the extractive industry, specifically focusing on innovative mining ventures. The research primarily investigates various determinants influencing project risks, including production efficiency, cost, informational content, resource potential, organizational structure, external environmental influences, and environmental impacts. In addressing the research challenge, system-cognitive models from the Eidos intellectual framework are employed. These models quantitatively reflect the informational content observed across different gradations of descriptive scales, predicting the transition of the modelled object into a state corresponding to specific class gradations. A comprehensive analysis of strengths, weaknesses, opportunities and threats (SWOT) has been conducted, unveiling the dynamic interplay of development factors against the backdrop of threats and opportunities within mineral deposits exploitation projects. This analysis facilitates the identification of critical problem areas, bottlenecks, prospects, and risks, considering environmental considerations. The application of this novel intelligent technology significantly streamlines the development process for mining investment projects, guiding the selection of ventures that promise enhanced production efficiency, cost reduction, and minimized environmental harm. The methodological approach adopted in this study aligns with the highest standards of academic rigour, ensuring consistency in the use of professional terminology throughout the article and adhering to the stylistic and structural norms prevalent in leading academic journals. By leveraging an intelligent, systematic framework for risk analysis, this research contributes valuable insights into optimizing investment decisions in the mining sector, emphasizing sustainability and economic viability.

Keywords: Automated system; Cognitive analysis; Eidos system; Mining industry; Risk analysis, Intelligent technology; Indonesia

1 Introduction

Business development trends bring to the fore the need to develop effective mechanisms for the functioning of industrial enterprises. The formation of a competitive strategy and the achievement of competitive advantages based on the use of the results of innovative activity become relevant [1, 2]. Innovative activity aims at providing a new level of interaction between production factors through the use of new scientific and technical knowledge. The basis of innovation activity is the development and effective use of innovative methods and means of mining. Innovations in industry are the application of new achievements in science and technology necessary to increase labor productivity, efficiency and productivity. The full implementation of innovative technologies in industry is hindered by a number of limiting factors [3–5]:

(i) Lack of close and effective communication between scientific research institutions and implementation structures, which leads to departmental disunity and inefficient implementation of projects;

(ii) Low funding rate with a concomitant decrease in scientific potential in industry;

(iii) Lack of a systematic and consistent process of introducing innovations into the industry, which often leads to economic damage and losses;

(iv) Lack of experience in lending to the innovative sector of industry;

(v) Lack of qualified personnel in the innovation industry.

Within the realm of global practices, foresight has emerged as a distinctive mechanism for the prediction of technological advancements. This methodology comprises an array of expert assessment techniques aimed at evaluating the long-term prospects for innovative development, pinpointing technological breakthroughs, and identifying both tactical and strategic competitive advantages. Further, it facilitates the construction of plans and the organization of initiatives designed to yield significant impacts on the economy and society [6, 7].

An investment and innovation strategy is understood as a model of interaction of all resources directed to tangible and intangible assets, allowing the system to set development priorities and achieve its goals, while achieving economic growth, sustainable competitive advantages in the market and a positive social effect [7, 8]. The ultimate goal of the innovation process is the commercial development of innovation and its cost-effective use. This is achieved in cases where research and development are focused on production from the very beginning, when there is a real opportunity to increase investment in the necessary material and technical resources, unify individual stages of the scientific and production cycle and determine in advance whether the innovation meets the requirements of production and the needs of consumers [9].

The risk of an investment project in the mining industry is determined by the following factors: productivity, production cost, the degree of information content of the project, the resource potential of minerals, the organizational structure, the influence of the external environment, and the environmental impact determined by the threats of environmental pollution in the course of production activities [10]. Intelligent risk analysis in the mining industry refers to the systematic process of assessing and evaluating potential risks associated with extracting natural resources such as oil, gas, minerals, and metals. This involves utilizing advanced technologies and data analytics to predict and mitigate potential hazards that could impact operations, safety, and overall profitability. By integrating cutting-edge tools such as artificial intelligence, machine learning algorithms, and predictive modeling techniques, companies in the mining industry can make informed decisions regarding exploration, mining activities, environmental impacts, regulatory compliance, market volatility, and geopolitical factors [11, 12]. This proactive approach not only helps companies identify and address vulnerabilities but also enhances their ability to capitalize on new opportunities by anticipating challenges before they arise. In a volatile industry prone to economic fluctuations and unforeseen events, intelligent risk analysis serves as a crucial tool for promoting sustainable growth and ensuring long-term success.

Indonesia has a diverse economy, with developed industries in various sectors. The main sectors of the Indonesian economy are the extraction of natural resources, industry, agriculture, tourism, and information technology [13–15]. The country has developed industries such as textile, electronics, chemical, automotive, steel and food industries. Industry in Indonesia makes up a significant part of its economy. Indonesia is a major producer of agricultural products, including rice, coffee, cocoa, rubber, palm oil, fruits and vegetables. Agriculture plays an important role in the country's economy and provides employment for a significant part of the population [14]. Indonesia is one of the largest producers of oil and natural gas, and also has rich reserves of coal, copper, gold, silver and other minerals. According to the Global Mining Development Report 2019, Indonesia's proven crude oil reserves are 97.5 billion barrels, natural gas reserves are 3.2 trillion cubic feet, coal reserves are 37,000 million tons, ore and non-metallic mineral reserves are 2,052,902,5000 tons.

Investors, when investing in natural resources, should take into account the risk tolerance of projects, as some investments may require a longer period of time or have higher risks. In Indonesia, there are no political, social or economic risks to investing in the mining industry, because the country has an effective government, which ensures political stability and respects the rule of law [16, 17]. The real gross domestic product per capita is growing in the country, and the freedom of business and labor, as well as investment freedom, is ensured. In the early stages of selecting an innovative project, it is necessary to predict the volume of explored mineral resources, productivity and production costs. To ensure the required information content of the project, it is necessary to provide a compromise between the amount of necessary information and the cost of obtaining it. Excessively high costs for information content can reduce the technical and economic indicators of innovations.

One of the most significant characteristics of the mining industry is its relationship with the external environment [18]. The external environment can be characterized as the totality of factors influencing the activities of a mining enterprise, namely: consumers, competitors, government agencies, suppliers, financial institutions, sources of labor resources, as well as science, culture, the state of society and natural phenomena [19, 20]. In a market economy, the external environment is extremely dynamic, so its study allows the organization to rebuild its internal structure and adapt to changing conditions, which generally ensures operational efficiency and high competitiveness.

The organizational structure in the mining industry includes new high-performance equipment, systems of integrated mechanization and automation of production processes, logistics, management systems, methods and forms of organization, financing, crediting of production, and improved approaches to the training of qualified personnel [21–23]. Among the factors hindering the development of technological and product innovations in the mining industry are the lack of own financial resources, high rates on loans from commercial banks and the economic risk of developing new products. In addition, mining companies are experiencing a shortage of personnel with the required qualifications, and related industries are technologically unable to supply components and raw materials of the required quality [24, 25]. For the implementation of an innovative project, it is necessary to use additional materials (labor tools and equipment).

2 Research Methods

The methodological and instrument-technological basis of this research is automated system cognitive (ASC) analysis and the intellectual system "Eidos" (from the English word "cognition"). ASC analysis is a new promising mathematical and instrumental economic method, which is characterized by a universal non-parametric mathematical model based on semantic information theory, the presence of numerical calculation techniques and software tools that implement them [17, 26]. ASC analysis can be applied in all subject areas where a scientist or practitioner solves his professional problems and constantly improves his knowledge using the latest achievements in the field of artificial intelligence. ASC analysis enables the identification and study of types of cause-and-effect relationships between the composition of the system, internal structure, and apparent properties. Based on empirical data, formal models are created that quantitatively reflect the strength and direction of the influence of factor values on the behavior of the model system, especially its transition to different future states. The training database is loaded into the Eidos system, and an automated system-cognitive analysis is performed to extract information from the database and form knowledge from it. ASC analysis performs the following functions:

(i) Synthesis and adaptation of the semantic information model of the area, which includes the active control object and the environment.

(ii) Identification and prediction of the state of active controls, as well as the development of control actions to transfer the object to the specified target states.

(iii) In-depth analysis of the semantic information model of the subject area. Seven models are formed in the system, i.e., INF1-INF7. It is determined that one model has the highest reliability of the identification and non-identification of training sample objects.

The mathematical model of the ASC analysis and the Eidos system is based on the systematic mathematics of fuzzy intervals and enables a comparable treatment of large amounts of fragmented and noisy interdependent data presented at different types of scales (nominal, ordinal and numerical) and different units. of measurement. Based directly on empirical data, the matrix of absolute frequencies is calculated, as shown in Table 1. Based on this, the matrix of conditional and unconditional percentage distributions is calculated, as shown in Table 2. Then, based on Table 2, the matrices of system cognitive models are calculated in Table 3.

Table 1. Matrix of absolute frequencies (ABS statistical model)

		Classes					Sum
		1	...	j	...	W	
Factor values	1	N_{11}		N_{1j}		N_{1W}	
	...						
	i	N_{i1}		N_{ij}		N_{iW}	$N_{i\Sigma} = \sum_{j=1}^{W} N_{ij}$
	...						
	M	N_{M1}		N_{Mj}		N_{MW}	
Total quantity signs by class				$N_{\Sigma j} = \sum_{i=1}^{M} N_{ij}$			$N_{\Sigma\Sigma} = \sum_{i=1}^{W} \sum_{j=1}^{M} N_{ij}$
Total quantity learning objects samples by class				$N_{\Sigma j}$			$N_{\Sigma\Sigma} = \sum_{j=1}^{W} N_{\Sigma j}$

Table 2. Matrix of conditional and unconditional percentage distributions (statistical models PRC1 and PRC2)

		Classes					Unconditional Probability Sign
		1	...	j	...	W	
Factor values	1	P_{11}		P_{1j}		P_{1W}	
	...						
	i	P_{i1}		$P_{ij} = \frac{N_{ij}}{N_{\Sigma j}}$		P_{iW}	$P_{i\Sigma} = \frac{N_{i\Sigma}}{N_{\Sigma\Sigma}}$
	...						
	M	P_{M1}		P_{Mj}		P_{MW}	
Unconditional probability class				$P_{\sum_j}$			

Table 3. System cognitive model matrix

		Classes 1	...	j	...	W	Significance Factor a
Factor values	1	I_{11}		I_{1j}		I_{1W}	$\sigma_{1\Sigma} = \sqrt[2]{\frac{1}{W-1}\sum_{j=1}^{W}\left(I_{1j}-\bar{I}_1\right)^2}$
	...						
	i	I_{i1}		I_{ij}		I_{iW}	$\sigma_{i\Sigma} = \sqrt[2]{\frac{1}{W-1}\sum_{j=1}^{W}\left(I_{ij}-\bar{I}_i\right)^2}$
	...						
	M	I_{M1}		I_{Mj}		I_{MW}	$\sigma_{M\Sigma} = \sqrt[2]{\frac{1}{W-1}\sum_{j=1}^{W}\left(I_{Mj}-\bar{I}_M\right)^2}$
Unconditional probability class		$\sigma_{\Sigma 1}$		$\sigma_{\Sigma j}$		$\sigma_{\Sigma W}$	$H = \sqrt[2]{\frac{1}{(W \cdot M-1)}\sum_{j=1}^{W}\sum_{i=1}^{M}\left(I_{ij}-\bar{I}\right)^2}$

Designations in tables are as follows:
i: the value of the past parameter;
j: the value of the future parameter;
N_{ij}: the number of occurrences of the j-th value of the future parameter with the i-th value of the past parameter;
M: the total number of values for all previous parameters;
W: the total number of values for all future parameters;
N_i: the number of occurrences of the i-th value of the passed parameter in the whole sample;
N_j: the number of occurrences of the j-th value in the entire sample of the future parameter;
N: the number of occurrences of the j-th value of the future parameter with the i-th value of the previous parameter in the entire sample;
I_{ij}: certain information criterion: the amount of information related to the observation of the i-th value of the past parameter, when the object goes to the state corresponding to the j-th value of the future parameter;
P_i: the relative frequency of fulfillment of the i-th value of the previous parameter in the unconditional training sample;
P_{ij}: conditional relative frequency of reaching the i-th value of the past parameter at the j-th value of the future parameter.

The essence of these methods is that the value of the factor calculates the amount of information that the modeling object moves to a state corresponding to a certain class during the activity. Based on ubiquitous cognitive models, the tasks of identification (classification, recognition, diagnosis, prediction), decision support and research of the model subject are solved by studying its ubiquitous cognitive model [27]. The risk of investment projects, productivity, production cost and content and mineral potential can be divided into five types, namely, very low, low, medium, high, and very high. The organizational structure, the negative impact of the external environment and the adverse effects on the natural environment can be divided into five types, namely, very low, low, medium, large, and very large. In the Excel environment, the file Imp_data.xls was compiled with the initial data, which is placed in the AID_DATA\Imp data directory. An example of a file with initial data is shown in Table 4. To input raw data into the Eidos system, the command 2.3.2.2 is activated and the input parameters are set, as shown in Figure 1. The 2022 version of the Eidos system can work with millions of objects, but the maximum dimension of the databases should be 4000 categories and 4000 factor scales. However, the dimension of the database is still limited, with a maximum of 4000 categories and 4000 factor scales. When "Recalculate scales and steps" and "Go to generate model" are selected, command 3.5 is run to synthesize and verify the models, as shown in Figure 2.

Table 4. Initial data for the study

Variant No.	IPR	PP	PC	IP	NR	OS	IEE	EP
Variant 1	very low	very low	very high	very low	very low	very low	very high	very high
Variant 2	low	low	high	low	low	low	high	high
Variant 3	medium	medium	medium	medium	medium	medium	medium	medium
Variant 4	high	high	low	high	high	high	low	low
Variant 5	very high	very high	very low	very high	very high	very high	very low	very low

The Eidos system automatically creates 10 mathematical models for each study and evaluates their reliability according to several criteria. Checking of semantic information models (evaluating their reliability or adequacy) can be done in Eidos system ASC analysis tools in different ways (internal and external validity and bootstrapping method). In this study, the number of types 1 and 2 errors, i.e., false detection errors, was calculated. The quality criteria of the obtained models are shown in the figure. Van Risbergen's F and L1 measurements, proposed by

Professor Lutsenko, were used to assess the reliability of the Eidos system models. Figure 3 shows the validity of the cognitive models of the system. Model INF7 has high object detection reliability.

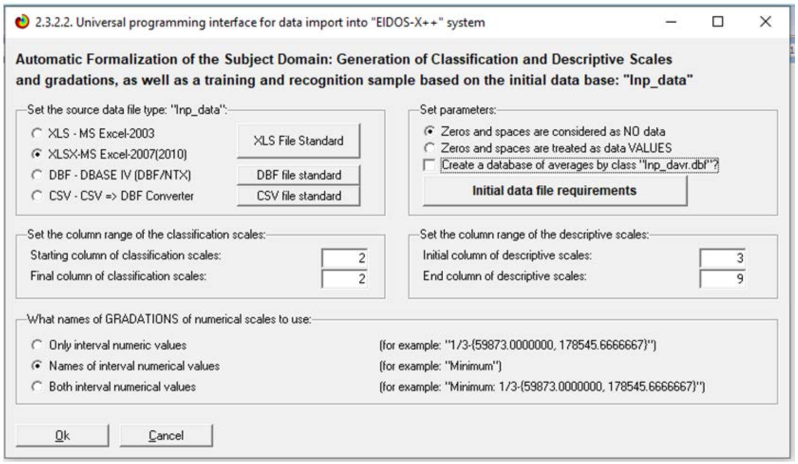


Figure 1. Setting the parameters for entering data into the system

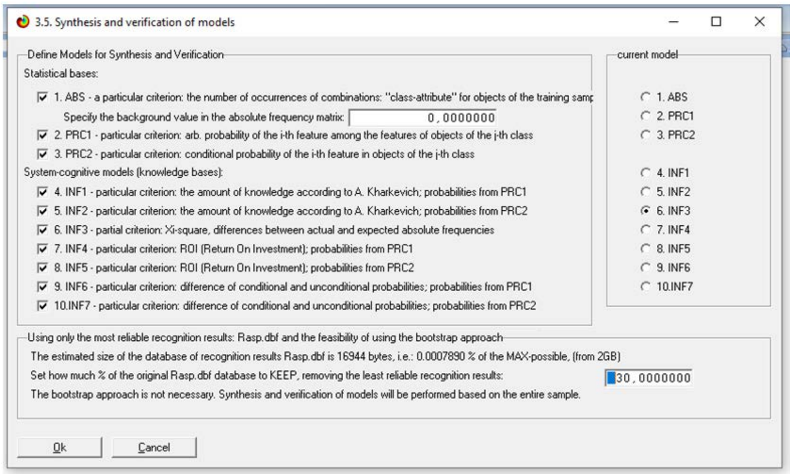
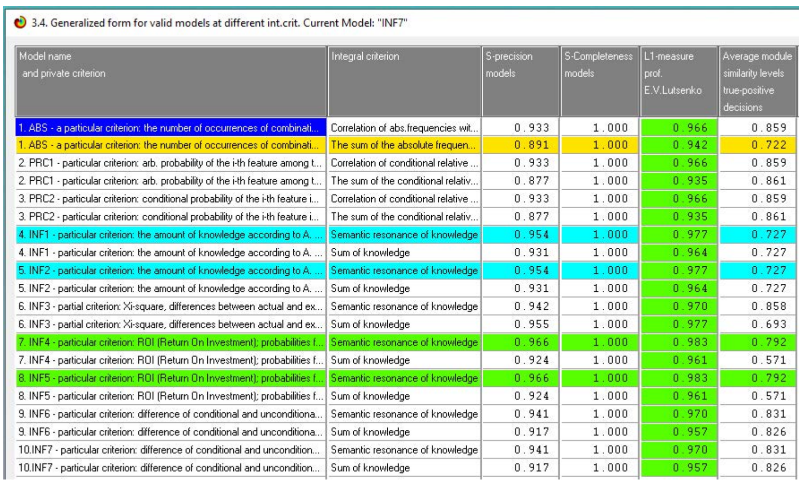


Figure 2. Selection of knowledge models


3.4. Generalized form for valid models at different int.crit. Current Model: "INF7"

Model name and private criterion	Integral criterion	S-precision models	S-Completeness models	L1-measure prof. E.V.Lutsenko	Average module similarity levels true-positive decisions
1. ABS - a particular criterion: the number of occurrences of combinati...	Correlation of abs.frequencies wit...	0.933	1.000	0.966	0.859
1. ABS - a particular criterion: the number of occurrences of combinati...	The sum of the absolute frequen...	0.891	1.000	0.942	0.722
2. PRC1 - particular criterion: arb. probability of the i-th feature among t...	Correlation of conditional relative ...	0.933	1.000	0.966	0.859
2. PRC1 - particular criterion: arb. probability of the i-th feature among t...	The sum of the conditional relativ...	0.877	1.000	0.935	0.861
3. PRC2 - particular criterion: conditional probability of the i-th feature i...	Correlation of conditional relative ...	0.933	1.000	0.966	0.859
3. PRC2 - particular criterion: conditional probability of the i-th feature i...	The sum of the conditional relativ...	0.877	1.000	0.935	0.861
4. INF1 - particular criterion: the amount of knowledge according to A. ...	Semantic resonance of knowledge	0.954	1.000	0.977	0.727
4. INF1 - particular criterion: the amount of knowledge according to A. ...	Sum of knowledge	0.931	1.000	0.964	0.727
5. INF2 - particular criterion: the amount of knowledge according to A. ...	Semantic resonance of knowledge	0.954	1.000	0.977	0.727
5. INF2 - particular criterion: the amount of knowledge according to A. ...	Sum of knowledge	0.931	1.000	0.964	0.727
6. INF3 - partial criterion: Xi-square, differences between actual and ex...	Semantic resonance of knowledge	0.942	1.000	0.970	0.858
6. INF3 - partial criterion: Xi-square, differences between actual and ex...	Sum of knowledge	0.955	1.000	0.977	0.693
7. INF4 - particular criterion: ROI (Return On Investment); probabilities f...	Semantic resonance of knowledge	0.966	1.000	0.983	0.792
7. INF4 - particular criterion: ROI (Return On Investment); probabilities f...	Sum of knowledge	0.924	1.000	0.961	0.571
8. INF5 - particular criterion: ROI (Return On Investment); probabilities f...	Semantic resonance of knowledge	0.966	1.000	0.983	0.792
8. INF5 - particular criterion: ROI (Return On Investment); probabilities f...	Sum of knowledge	0.924	1.000	0.961	0.571
9. INF6 - particular criterion: difference of conditional and unconditiona...	Semantic resonance of knowledge	0.941	1.000	0.970	0.831
9. INF6 - particular criterion: difference of conditional and unconditiona...	Sum of knowledge	0.917	1.000	0.957	0.826
10.INF7 - particular criterion: difference of conditional and uncondition...	Semantic resonance of knowledge	0.941	1.000	0.970	0.831
10.INF7 - particular criterion: difference of conditional and uncondition...	Sum of knowledge	0.917	1.000	0.957	0.826

Figure 3. Credibility of system-cognitive models

3 Results and Discussion

When the training sample is loaded into the Eidos system, it is necessary to start the study with an analysis of the information portrait of the features. In the process of compiling the training sample, additional redundant features may get into the descriptive features due to user errors. This can be digital data entered instead of characters, or digital data whose values exceed the specified range of features. Even an extra space in symbolic features is accepted by the Eidos system as a new feature. In multi-word features, the underscore character (_) is used to concatenate individual words. If some feature gradation has a zero influence value, then such gradation is not applied in the training sample. Obviously, such a training sample needs to be corrected.

The Eidos system was used to determine the feasibility of various investment projects in the mining industry. The degree of similarity of that specific object image is compared and determined with other specific object images or generalized class images, resulting in a classification of objects or classes in descending order. similarity to the identified object. According to the command 4.1.3.1 shown in in subgraph (a) of Figure 4, the similarity of the objects of the IPR_very_high class is determined, and the similarity degree of the objects of the IPR_very_low class is shown in in subgraph (b) of Figure 4. After executing command 4.1.2 and receiving informational portraits of the classes shown in Figure 5. A class data portrait is a collection of data and features collected and analyzed by the Eidos intelligent system. Such a portrait contains information about the strength and direction of the influence of signs on the risk assessment of an investment project. In particular, the researcher must identify precisely those characteristics that have the greatest impact on the condition of the class. In general, the information portrait of the class can help the researcher to select the most important features and reduce the complexity of the risk assessment of the investment project.

The risk of investment projects in the mining industry is very high if the information content, productivity, resource potential and organizational structure are very low, and the negative impact of the external environment, production cost and adverse effects on the natural environment are very high.

The risk of investment projects in the mining industry is very low if the productivity, resource potential, information content and organizational structure are very high, and the adverse effects on the natural environment, the negative impact of the external environment and production cost are very low.

The data images of the objects shown in Figure 6 were obtained using command 4.3.1. It was observed that the "high" gradation on the production cost scale significantly influences the risk associated with the investment project, as evidenced by an Impact of Production Risk (IPR) value of 71.542. Figure 7 shows the Pareto curve indicating the importance of descriptive scales (attributes). It is noted that 37% of the attributes deemed most critical contribute to 50% of the aggregate importance. Similarly, the top 50% of attributes are responsible for 65% of the overall significance. The graph grows monotonically without a saturation region, emphasizing the state when there are no redundant features in the problem.

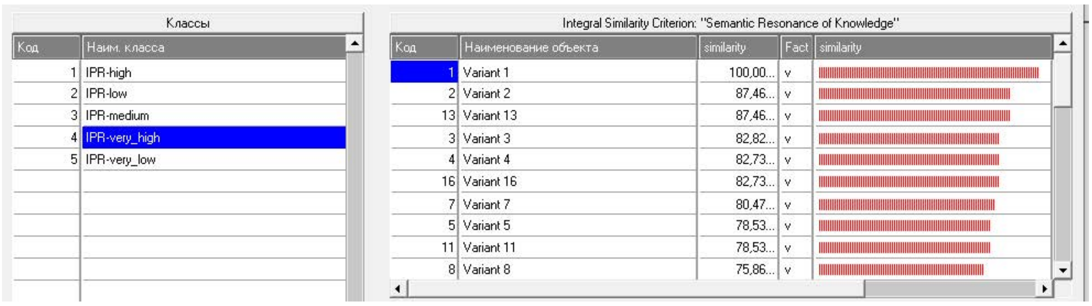
SWOT analysis is a widely known and recognized method of strategic planning. Many specialists perform it informally (intuitively), based on their professional experience and competence. But the possibilities of experts have their limitations and often, for various reasons, they cannot and do not want to do this. Thus, there is a problem with conducting a SWOT analysis without the involvement of experts. This problem in the Eidos intellectual system is solved by automating the functions of experts, that is, measuring the strength and direction of the influence of factors directly on the basis of empirical data.

The preparation of data for the SWOT analysis of the IPR_very_high class is shown in Figure 8. The results of the SWOT analysis were obtained by executing command 4.4.8. Data preparation and results of the SWOT analysis of the IPR_very_low class are shown in Figure 8.

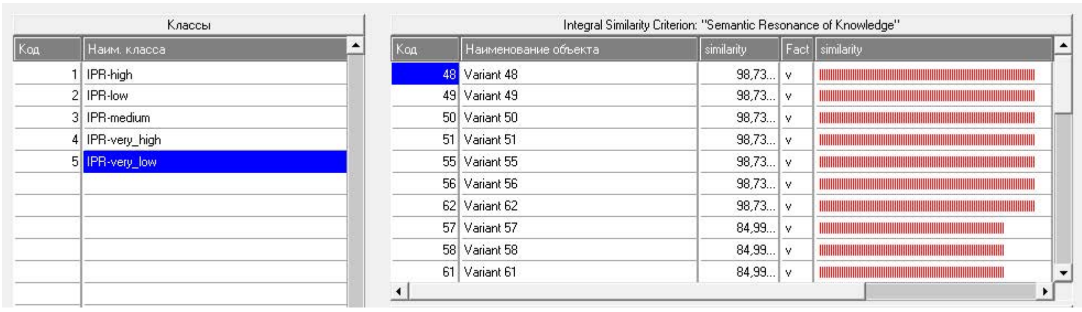
According to the results of the SWOT analysis, attention must be paid mainly to those factors that most influence the transition of the class to a certain state. The SWOT analysis includes an analysis of the strengths and weaknesses of the development of the object being studied in their interaction with threats and opportunities, and it also allows identifying current problems, bottlenecks, opportunities and threats, considering the most important factors.

Non-local neurons make it possible to display in visual form the system for determining the future states of an object. A non-local neuron represents the future state of the control object with the image of the factors most strongly influencing it, indicating the strength and direction (promotes or hinders) of their influence. Figure 9 shows a non-local neuron of the IPR_very_high class and the data preparation for its formation. Figure 10 shows a non-local neuron of the IPR_very_low class and the data preparation for its formation.

Using non-metric integral criteria, which are accurate for non-oratories spaces, the distances between clusters are calculated based on the entire amount of information about an object's cluster membership that is included in its system of features. A Pareto subset of a non-local integrated map in the INF7 model with two neurons is seen in Figure 10. These are 53.53% of the most important synoptic relationships. The forces of influence of factors are indicated on the links, with activating links in red, and inhibitory links in blue. The Pareto subset of the non-local neural network contains five neurons corresponding to the gradations of the risk class of investment projects. The network takes into account 63.53% of the most significant synoptic links.

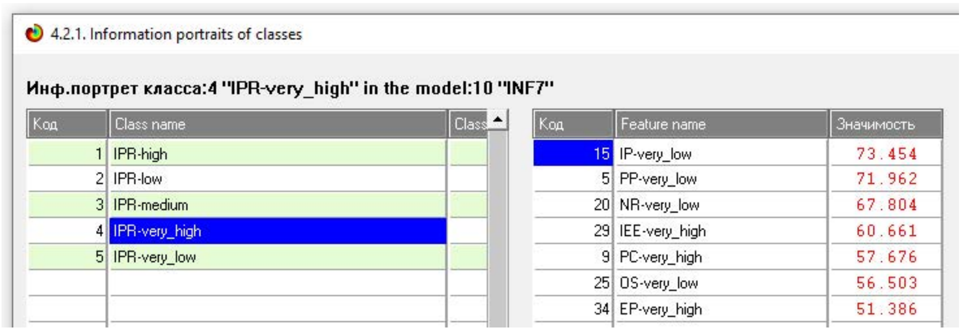


(a)

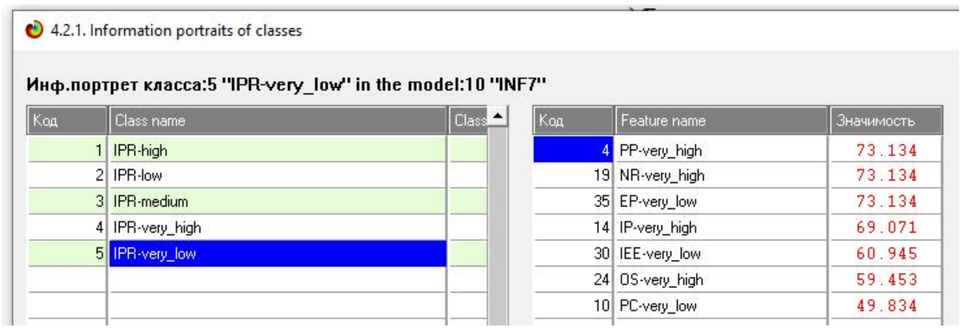


(b)

Figure 4. Visualization of the results of object recognition. (a) Class IPR_very_high; (b) Class IPR_very_low



(a)



(b)

Figure 5. Information portraits. (a) Class IPR_very_high; (b) Class IPR_very_low

Clustering is an automatic classification operation in which objects are combined into groups (clusters) in such a way that differences between objects are minimal within groups and maximal between groups. Clustering determines not only the composition of clusters, but also their sets and boundaries. Figure 7 shows that all classes form two opposite clusters, which are the poles of the construct, according to the system of values of the characteristics that determine them. The construction poles are also divided into sub-clusters. Cluster analysis reduces the number of factors used when performing a study.

Figure 6. Influence of the gradation of the feature cost of production on the risk of the project

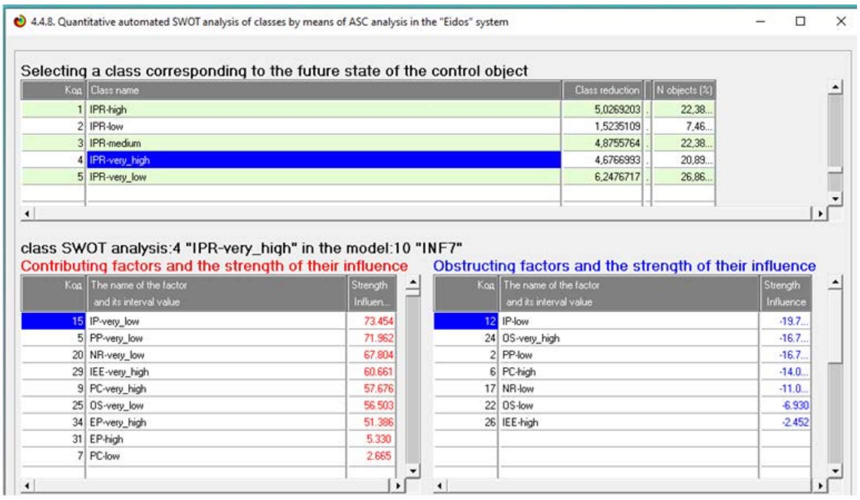


Figure 7. Preparing data for SWOT-analysis of the IPR_very_high class

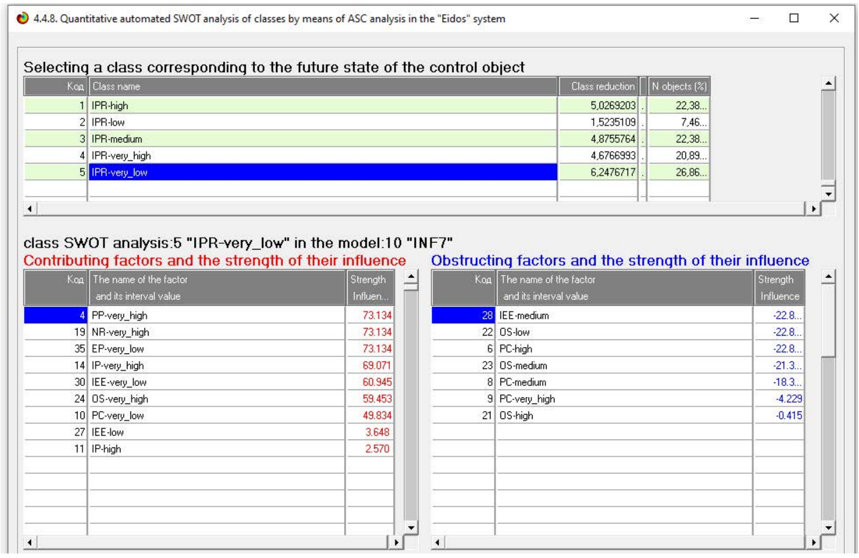


Figure 8. Preparing data for SWOT analysis of the IPR_very_low class

The Eidos system's step-by-step alteration of the interclassed distance with cognitive feature grouping is seen in Figure 10. Using non-metric integral criteria, which are accurate for non-oratories spaces, the distances between clusters are calculated based on the entire amount of information about an object's cluster membership that is included in its system of features. A Pareto subset of a non-local integrated map in the INF7 model with two neurons is seen in Figure 9, which shows 53.53% of the most important synoptic relationships.

To perform an intellectual risk analysis of an investment project in the mining industry, a debugged training sample (database) needs to be uploaded to the Eidos system. Then the initial data on the project in a particular field needs to be added. In the Eidos system, it is necessary to perform an ASC analysis because the result classifies the predicted risk level of the project being implemented [28].

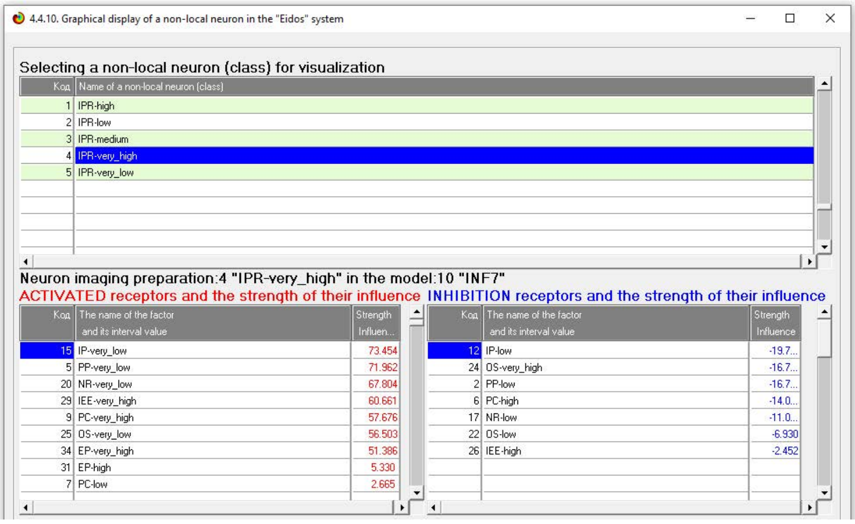


Figure 9. Preparing data for a non-local neuron of class IPR_very_high

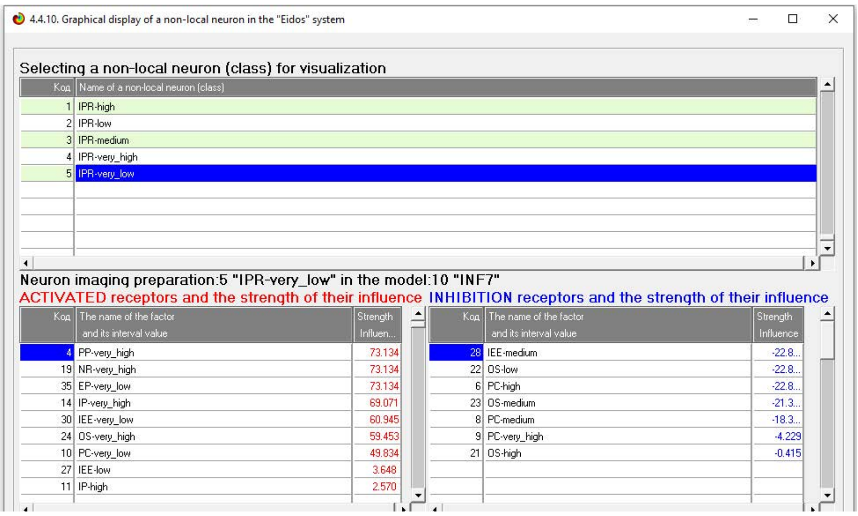


Figure 10. Preparing data for a non-local neuron of class IPR_very_low

The Eidos system's knowledge models are fuzzy declarative hybrid models that incorporate certain advantageous aspects of both neural network and frame models of knowledge representation. In this approach, classes represent neurons and frames, while signs represent receptors and spaces (slots being represented by descriptive scales). The Eidos system model deviates from the frame model of knowledge representation in that it employs an efficient and straightforward software implementation. This is achieved by distinguishing distinct frames only based on the information they contain rather than on a collection of slots and spaces.

The Eidos system model cannot be the same as the knowledge representation neural network model in that [29, 30]:

(i) The direct counting method, which is based on a well-theorized information theory model (similar to Bayesian networks), calculates the weight coefficients on the receptors instead of using the iterative backpropagation method;

(ii) The weight coefficients have a meaningful interpretation based on information theory that is well-substantiated.

The Eidos system visualizes non-local neurons as unique graphic shapes, where the dendritic color and thickness indicate the direction and intensity of the impact of neuron receptors on the degree of activation or inhibition. The method for predicting an object's future states may be seen visually thanks to non-local neurons [31–33]. The future state of the control object is represented by a non-local neuron, which indicates the intensity and direction of the variables that are significantly impacting it [34–36]. A neural network is a collection of interconnected neurons. In classical neural networks, communication between neurons is carried out by input and output signals. In non-local neural networks, communication is based on a common information field implemented by a semantic information model. The Eidos system provides the construction of any subset of a multilayer neural network with specified or selectable receptors and neurons connected to each other by links at any level of mediation.

There are 55 different ways that the Eidos system can function, which are too many to list in a single article [37].

The website https://www.patreon.com/user?u=87599532 has a series of open lectures that provide more in-depth information regarding the workings of the Eidos system [38–40]. Like every intellectual system, the Eidos system may be utilized by any user, provided he has functional databases, the building of which is a time-consuming and arduous task. Additionally, training datasets that are representative of several technical and medical data analysis applications have been created by the authors of this study. Upon request, readers of the publication can have free access to retrospective databases on the identification of human illnesses. A lot of time may be saved by health professionals when creating training databases.

4 Conclusions

The analysis conducted using the Eidos system has revealed considerable variability in the similarity of risk profiles across investment projects within the mining industry. For projects classified under high gradation, risk similarity scores range between 70.14 and 98.75; for those categorized as low gradation, the range is from 69.22 to 91.03; medium gradation projects exhibit a range from 72.03 to 97.71; very high gradation projects span from 65.10 to 100.00; and very low gradation projects show a range from 77.44 to 99.73. Through the systematic analysis of the system-cognitive model, recommendations can be derived for the strategic formation of control factors. Such factors are designed to ensure a minimized risk level for mining industry investment projects with a high degree of determinism. Furthermore, it has been observed that the adoption of innovative activities within the mining sector not only enhances the intensification of mining production and labor productivity but also leads to significant additional profits.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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