Models and technologies of cognitive agents for decision-making with integration of Artificial Intelligence

Yuliia Kostiuk[†], Pavlo Skladannyi[†,*], Volodymyr Sokolov[†] and Maksym Vorokhob[†]

Borys Grinchenko Kyiv Metropolitan University, 18/2 Bulvarno-Kudryavska str., 04053 Kyiv, Ukraine

Abstract
Cognitive agent models and technologies integrated with artificial intelligence are key in modern research that contributes to developing adaptive decision support systems. Cognitive agents capable of self-learning use neural networks and deep learning algorithms to effectively process large amounts of information and predict and analyze complex, multi-criteria situations. Such agents adapt to changing conditions thanks to built-in self-learning mechanisms and natural language processing. They can interact with users at a level that is as close as possible to human communication. In addition, using cognitive maps and other thinking models allows us to create systems that visualize cause-and-effect relationships and integrate subjective factors, such as experience and intuition, into the decision-making process. This makes it possible to ensure high accuracy, flexibility, and efficiency of decisions in complex scenarios that require dynamic adaptation and real-time data processing. Integrating artificial intelligence into cognitive systems opens up new opportunities for creating intelligent decision-support tools capable of detecting patterns in user behavior and recommending optimal actions based on predictions, which increases the efficiency of decision-making in complex multi-criteria situations.

Keywords
Cognitive agents, artificial intelligence, decision-making, neuro-fuzzy networks, neural networks, fuzzy logic, integration, optimization methods

1. Introduction

The integration of cognitive agents into Decision-Making Processes (DMPs) using Artificial Intelligence (AI) allows for the creation of adaptive systems that are capable of analyzing a large amount of heterogeneous information and supporting decision-makers [1, 2]. A key feature of such agents is the ability to consider the intuition and experience of the decision-maker, which ensures the objectivity of decisions [3, 4]. For this, deep learning technologies, neural networks, and natural language processing are used to improve user interaction [5, 6]. Cognitive agents use symbolic and imaginative thinking through semantic networks and mental maps, allowing them to visualize cause-and-effect relationships and adapt to changes in real time [7]. Machine learning algorithms help detect patterns in user behavior and recommend optimal actions based on context [8].

The integration of AI allows the creation of new decision-making support tools that contribute to detecting and predicting critical situations in real-time [9]. The reliability of decisions made using cognitive agents depends on the quality of data and the ethical aspects. It is essential to develop regulatory frameworks to ensure the transparency of algorithms and risk assessment [2, 10]. These systems adapt to changes and increase the accuracy of decisions by combining neural and symbolic approaches [7]. Modern cognitive maps and neural networks implement decision-making mechanisms that, considering the individual cognitive characteristics of the Mental Status Assessment (MSA), ensure effective adaptation to changing conditions. This approach allows the creation of systems with high accuracy, flexibility, and adaptability, which is vital in complex multi-criteria scenarios [5, 11, 12]. Therefore, modern models of cognitive agents for decision support with the integration of AI are based on the synergy of neural methods and language processing [2, 13]. This allows us to create systems that adapt to changing conditions and improve the accuracy and efficiency of decisions in complex situations that require intelligent processing and adaptation.

MoDaST 2025: Modern Data Science Technologies Doctoral Consortium, June, 15, 2025, Lviv, Ukraine
* Corresponding author.
† These authors contributed equally.
y.kostiuk@kubg.edu.ua (Y. Kostiuk); p.skladannyi@kubg.edu.ua (P. Skladannyi); v.sokolov@kubg.edu.ua (V. Sokolov); m.vorokhob@kubg.edu.ua (M. Vorokhob)
0000-0001-5423-0985 (Y. Kostiuk); 0000-0002-7775-6039 (P. Skladannyi); 0000-0002-9349-7946 (V. Sokolov); 0000-0001-5160-7134 (M. Vorokhob)

2. Analysis of literary sources

The development of models and technologies that combine cognitive agents' capabilities with AI's achievements allows for the creation of adaptive, intelligent systems for effective decision-making in complex multi-criteria conditions. Research, in particular, the work of H. Han, Z. Li, B. Sahoh, B. Igoche, M. Usman, and T. Hovorushchenko, focuses on the integration of cognitive maps and neural networks [1, 2, 6, 12, 14], which allows achieving new levels of adaptability and accuracy in real-time. H. Han and M. Usman investigated the use of deep learning to improve the self-learning of cognitive agents [1, 12], B. Sahoh and L. Yu worked on the creation of models that integrate cause-and-effect relationships [2, 19], and the work of B. Igoche and T. Hovorushchenko focuses on natural language processing to improve the interaction of agents with users [6, 14].

Research from overseas scholars in [16], such as Y.X. Zhong, J. Pearl, G. Hinton, G. Klein, W. Tang, D. Nallaperuma, also significantly contribute to the development of this field [3–5, 7, 8, 10, 11, 16]. J. Pearl explores the ethical aspects of AI in decision-making, and D. Mackenzie focuses on causal models that allow agents to detect connections between actions and their consequences [7, 11]. G. Klein and D. Nallaperuma emphasize the integration of intuition and people's experience into AI systems [3, 4], which makes the DMP more accurate and adaptive to real conditions. One of the important achievements is the creation of models that combine neural networks and natural language processing, which allows cognitive agents to adapt to changing conditions and provide a high level of prediction and visualization [5, 6, 10, 12, 14, 17], which is key to effective management of complex situations.

Thus, the development of cognitive agents with the integration of AI is based on the synthesis of modern technologies, which allows the creation of systems capable of processing large amounts of data, predicting critical situations, and making informed decisions, taking into account both objective and subjective aspects of the activity.

3. Research methods

The development of models of cognitive agents for decision-making with the integration of AI involves using algorithmic approaches and conceptual models that consider the human factor. The key is using decision support systems (DSS), which integrate machine learning methods, particularly neural networks, for real-time data analysis. Neural network training algorithms improve the accuracy and speed of decision-making by detecting patterns in large amounts of data [5, 6, 15]. Such agents can adapt to new situations through self-learning.

Integrating AI into cognitive systems also includes natural language processing (NLP) to improve user interaction [6, 14]. Hybrid models of cognitive agents that combine Mamdani-Zadeh fuzzy logic and neural networks allow efficient work with fuzzy data and optimize DMPs. This provides flexibility and adaptability when solving complex multi-criteria problems in changing conditions.

4. Presentation of the primary material

Cognitive agent models with AI integration evolve through agent-oriented approaches combining neuro-fuzzy technologies for flexible data processing. Model synthesis tools integrating knowledge in images improve learning and DMPs [16]. The subject-oriented approach allows systems to be adapted to the needs of the decision-making object, integrating cognitive models that can respond to changing conditions [7]. Using mental maps and fuzzy schemes improves assessing the impact of events and interaction with AI [2]. This allows for increased accuracy of forecasting and adaptation to new situations.

Integrating cognitive properties in AI creates mechanisms for accelerated thinking and adaptive models that contribute to the optimization of processes and increase the efficiency of decision-making in complex situations [12]. Methods for synthesizing neuro-fuzzy models of cognitive agents with mental and intentional characteristics use hybrid models such as "cognitive processing module, neural network, the genetic algorithm," as well as a modification of the Mamdani-Zadeh fuzzy system [5] (Fig. 1).

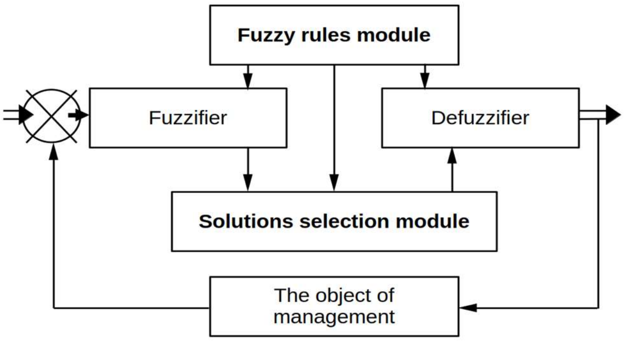

Figure 1: Hybrid model of a cognitive agent using Mamdani-Zadeh fuzzy logic

To ensure the high efficiency of such models in complex and changing conditions, it is vital to apply a hybrid approach that combines Mamdani-Zadeh fuzzy logic with other optimization methods, in particular neural networks and genetic algorithms [1]. A hybrid model of a cognitive agent using fuzzy logic allows it to adapt to conditions where information is incomplete or fuzzy and make decisions that consider various possible scenarios. A critical component of this model is the cognitive processing module, which performs the task of fuzzification, transforming precise input data into fuzzy sets, which are then processed using fuzzy logic [5]. Next, the results are defuzzified, which allows us to transform the obtained fuzzy data into specific solutions that can be used for decision-making in real conditions. The interaction between neural networks, genetic algorithms, and fuzzy logic allows us to create an adaptive system that quickly responds to changes in external conditions and makes optimal decisions even under uncertainty. Using such a hybrid model enables cognitive agents to improve the efficiency of processing complex and variable data and to ensure a high level of adaptation and prediction in constantly changing environments [11].

The aggregation of fuzzy sets for decision-making in cognitive agents is the process by which different fuzzy sets representing different aspects or decision options are combined to obtain a final result [15]. In cognitive agents using fuzzy logic, this process is an essential step in decision-making, as it helps to consider all possible options and incomplete or fuzzy data coming from different sources. The process of fuzzy set aggregation involves combining multiple fuzzy rules and values derived from different input parameters into a single solution. This is done by applying a logical sum, which allows us to consider each parameter's influence, regardless of whether it is clear or fuzzy. The logical sum will enable us to summarize all possible values, considering their significance, which makes the process more flexible and adaptive to changing conditions [3, 6].

To increase the efficiency of aggregation, membership function weighting is used. This allows each parameter to receive a certain weight depending on its importance, which allows for a more accurate determination of the result. Additionally, using singletons or Gaussian functions simplifies the calculations: instead of complex integration, the values of the sets can be summed. Thus, fuzzy set aggregation is an essential tool in decision-making, as it allows cognitive agents to make informed decisions by combining various fuzzy data, taking into account their significance, and ensuring adaptability and accuracy of the result in conditions of uncertainty or complex situations (Fig. 2) [23].

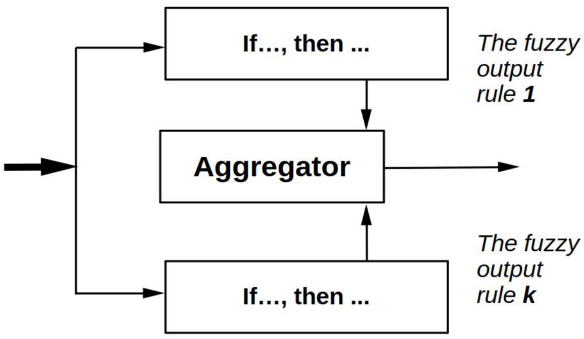

Figure 2: Aggregation of fuzzy sets for determining the result in cognitive agents

Cognitive agent models for decision-making with the integration of AI process fuzzy information using linguistic “If P, then C” rules that contain conditions, actions, and weights W_i. The decision-making module analyzes the contribution of fuzzy values using fuzzy logic algorithms. The membership function $\mu p_i(x)$can take values from 0 to 1, where 1 means complete compliance of the parameter, and 0 means complete non-compliance. At the fuzzification stage, the input data P_i is converted into fuzzy values using the function $\mu p_i(x)$:

$$P_i = \mu p_i(x). \tag{1}$$

For cognitive agents that use the integration of fuzzy logic and AI methods for decision-making, each rule in the system has a weight coefficient that determines its importance. Logical conditions are formulated as "If $P_i$and P_j, then C_i", where the parameters P are fuzzified [15]:

$$R_i = W_i \cdot \mu p_i(x). \tag{2}$$

Weights W_i determines the importance of each rule for the input parameters. The results are calculated through defuzzification, which converts the membership function into the value of the output parameter C_i, W_i. The defuzzification process is optimized by weighting the membership functions and using singletons or Gaussians, simplifying the initial solution's calculation. For this, the center of gravity is used, which allows calculating the resulting value [2, 3]:

$$C = \frac{\sum_{i=1}^{n} W_i \cdot \mu p_i(x)}{\sum_{i=1}^{n} W_i}, \tag{3}$$

where P_i is fuzzy parameters at the input, C is the output fuzzy parameter, $\mu p_i(x)$ is membership function for the input fuzzy parameter P_i, which determines the degree of fulfillment of the rule condition, which determines the degree of rule fulfillment for a certain value x, W_i is the weight coefficient that determines the importance of the i^{th} rule. Thus, cognitive agents integrate fuzzy logic methods, weighting coefficients, and optimization algorithms, ensuring high data analysis efficiency and adaptability in complex information environments. To optimize the defuzzification process in cognitive agents, the pre-weighting of membership functions is used through fuzzy set intersection operations and singleton or Gaussian-type functions. This allows simplifying the calculations by replacing integration with simple summation [5]:

$$C \approx \sum_{i=1}^{n} R_i, \tag{4}$$

where $R_i = W_i \cdot \mu p_i(x)$,$R_i$ is the contribution of the i^{th} rule to the overall score, W_i is the weight coefficient of the i^{th} rule, indicating its significance, $\mu p_i(x)$ is membership function for the input fuzzy parameter P_i, which determines the degree to which this rule is fulfilled for a certain value x. Thus, cognitive agents make decisions by integrating fuzzy logic methods, weight coefficients, and optimization algorithms, ensuring high data analysis efficiency and adaptability in complex information environments [3, 12].

At the design stage of the decision-making module, the expert sets the initial parameter values, after which the optimal range is searched for each adjustable parameter to increase the efficiency of the cognitive processing module (Fig. 3). This leads to the need to optimize the internal parameters of the fuzzy network by searching for the optimal set of values. Features of tuning the fuzzy network include the integration of machine learning algorithms for automatic adjustment of parameters, which allows for achieving higher accuracy in the DMP and increasing the system's overall efficiency.

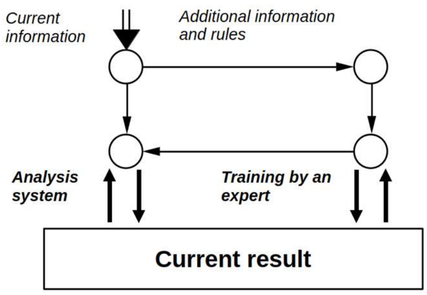

Figure 3: The process of configuring a fuzzy network for decision making

This considers the interaction of linguistic rules and fuzzy parameters, allowing for more accurate modeling of real processes. Defuzzification is reduced to calculating the result at the output of the cognitive processing module, considering the weight of the rules and the significance of the parameters that determine the final impact on the system. The formula for calculating the result is:

$$Y = \frac{\sum_{i=1}^{n} W_i \sum_{j=1}^{k_i} W_{IJ} \cdot C_{IJ}}{\sum_{i=1}^{n} W_i \sum_{j=1}^{k_i} W_{IJ}}, \tag{5}$$

where Y is effective influence, C_{IJ} is a formative parameter that determines the center of the singleton, i.e., the fuzzy concept of a linguistic rule, W_i is the weight of the linguistic rule, W_{IJ} is the significance of the indicators of the group of fuzzy concepts of one rule. In the modification of the architecture of the fuzzy system, the use of neural networks for parameter adaptation is proposed, which allows more effectively taking into account the significance of various indicators, increasing the accuracy of decision-making and ensuring more flexible adaptation to changing conditions. Modifying the architecture of the fuzzy cognitive processing module involves the integration of additional technologies, such as neural networks, to adapt parameters and increase the efficiency of the cognitive processing module in conditions of uncertainty and variability of input data. In particular, the implementation of neural networks allows us to consider the significance of various indicators of fuzzy concepts, increasing the model's accuracy and adaptability. This provides more efficient information processing, reducing computational costs and ensuring better processing of complex and multidimensional input parameters. This approach allows us to improve the quality of decisions made within the framework of cognitive agents integrated into systems where it is necessary to process fuzzy information and consider expert knowledge (Fig. 4).

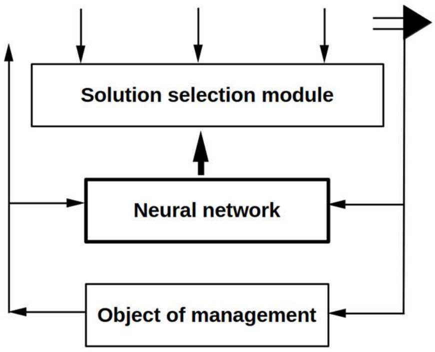

Figure 4: Modification of the architecture of the fuzzy cognitive processing module for cognitive agents with the integration of artificial intelligence in decision-making systems

The cognitive agent model for decision-making integrates fuzzy systems and neural networks, effectively using linguistic rules to incorporate expert knowledge, which increases agents' accuracy and adaptability. This combination forms neuro-fuzzy systems with increased efficiency and functional equivalence since the advantages of both approaches are combined - the flexibility of fuzzy systems and the ability of neural networks to self-learn. The training of neural networks in such a system is implemented through evolutionary algorithms that optimize the parameters of neurons in the hidden layer, which reduces computational costs, increasing the speed of learning and accuracy of the model [1]. The process includes optimizing clusters of input features and tuning the output layer, which can be carried out through gradient methods or singular scheduling. Cooperative learning distributes tasks between neurons, preventing duplication of functions and significantly accelerating the system's convergence [16]. Evaluating the efficiency of network elements using the defuzzification function allows us to improve the parameters without the need to train the original elements, increasing the model's overall efficiency and stability [7].

You can use the membership function and fuzzy inference operators to integrate linguistic rules into a fuzzy system, which translates uncertain and fuzzy data into a formalized model. If $\mu(x)$ is a function of the membership of the element in the fuzzy set, then the linguistic rule can be expressed through fuzzy logic operators as follows:

$$R\text{: IF } x_1 \text{ IS } A_1 \text{ AND } x_2 \text{ IS } A_2 \text{ THEN } y \text{ IS } B, \tag{6}$$

where A_1, A_2 and B are linguistic terms describing fuzzy sets, $\mu(x_1), \mu(x_2)$ and $\mu(y)$ are a membership function for input and output variables. In this context, fuzzy logic allows us to consider values that do not have clear boundaries or are incomplete, which significantly improves the system's ability to work with real, complex conditions and provides more flexible decision-making in cognitive agents with the integration of AI.

The mathematical equivalence can be expressed through the combination of a Mandami fuzzy system and a neural network, where the Mandami fuzzy system provides a formalization of knowledge in the form of linguistic rules that define the relationships between input and output variables. In contrast, the neural network is used for adaptive learning and parameter optimization, which allows complex, nonlinear dependencies to be modeled. This combination enables the integration of symbolic knowledge from fuzzy logic, which characterizes the fuzziness and uncertainty in data, with the capabilities of neural networks to adapt to changing conditions, which, in turn, increases the system's effectiveness in the DMP in complex, dynamic environments. The combination of these two approaches allows for significantly improving the accuracy and stability of predictions, which are critical for applications in cognitive agents and the integration of AI in complex information and control systems

$$f_{\text{neuro-fuzzy}}(x) = f_{\text{fuzzy}}(x) + f_{\text{neuro}}(x), \tag{7}$$

where $f_{\text{fuzzy}}(x)$ are linguistic terms, $f_{\text{neuro}}(x)$ are membership functions for input and output variables.

The search for optimal parameters of neurons in the hidden layer of a neural network can be effectively expressed by minimizing the loss function, using evolutionary algorithms that allow, based on the principles of natural selection, to improve the network parameters gradually. In particular, evolutionary algorithms, such as genetic or optimization algorithms that use differential combinations of parameters, can use the population search mechanism, where each set of parameters represents a separate "solution" that is evaluated using the loss function. As part of this process, the most effective parameters are selected, which are then combined and modified using data mixing operations and random parameter changes, contributing to generating new, potentially better options for settings. Thus, evolutionary algorithms make it possible to find global optimal parameters for hidden layers, which significantly improves the efficiency of training a neural network in complex and multidimensional optimization problems where traditional methods may be ineffective

$$\min_{\theta} L\,(\theta) = \sum_{i=1}^{N} (y_i - f(\,x_{i,}\theta))^2, \tag{8}$$

where θ is the neural network parameters, x_i is input data, y_i is target values, $f(x_{i,}\theta)$ is an activation function.

To find optimal weights and thresholds in a neural network within the framework of cognitive agent models integrated with AI, a strategic approach with cooperative search can be applied, which assumes that each neuron calculates its parameters independently of the others, which allows for the reduction of the interdependence between network elements and reduce the complexity of optimization processes. This approach allows each neuron to perform local optimizations based on its information, which will enable it to effectively adjust the parameters without simultaneously needing global processing of all network parameters. This reduces the computation time and increases the system's scalability, especially in conditions of a large number of parameters, and can also help adapt the neural network to changing external conditions or new data. Accordingly, the strategic approach allows for parallel optimization, which speeds up the learning process and improves the efficiency of the network in real applications [5]

$$W_{\text{opt}} = \arg\min \left(\sum_{i=1}^{N} (y_i - f(\,x_{i,}W))^2 \right), \tag{9}$$

where W is the weight of neurons optimized for each element.

The assessment of the effectiveness of the elements of the neuro-fuzzy network within the framework of cognitive agents for decision-making is carried out through the use of the defuzzification function, which allows us to convert fuzzy values obtained as a result of the analysis of complex systems into specific numerical outputs that can be used for further calculations or classification, which, in turn, allows us to reduce the level of uncertainty and increase the accuracy of decisions made in conditions of complex dynamic changes. Defuzzification in data analysis and classification allows cognitive agents to adapt to a constantly changing environment, improving the efficiency and reliability of decisions made by integrating fuzzy models that would enable you to process and adjust the information in real-time, even if it is incomplete or inaccurate.

$$\mu_{\text{output}}(y) = \max\,(\mu_{\text{class 1}}(y) + \mu_{\text{class 2}}(y) + \cdots), \tag{10}$$

where $\mu_{\text{class 1}}(y)$ is the membership function for class 1, and y is the value to be classified.

The learning strategy within the framework of cognitive agent models for decision-making integrated with AI is to maximize the efficiency of the hidden elements of the neural network without the need to learn the output parameters, which allows for a reduction in the amount of computational costs and increase the speed of adaptation of the network to new conditions. Such a strategy ensures the preservation of high performance with limited resources. Also, it allows optimization of the learning process, reducing the need for additional data or complex calculations to adjust the output parameters, which is essential for the effective operation of systems in real-time. The corresponding mathematical expression of this strategy can be written as the maximization of the efficiency function for the hidden elements $\max_h L(\theta)$:

$$\max_h L(\theta) = \sum_{i=1}^{N} f_{\text{hidden}}(x_i, h), \tag{11}$$

where h is the parameters of the hidden elements, $f_{\text{hidden}}(x_i, h)$ is the activation function for the hidden elements of the network, $L(\theta)$ is the loss function for these parameters.

Introducing the functional equivalence principle allows us to create an adaptive neuro-fuzzy network model that transforms the neural network learning algorithm into a fuzzy system. This allows us to apply optimization algorithms traditionally used for neural networks to fuzzy systems. Such integration will enable us to combine the advantages of neural networks, in particular their ability to adapt and learn from large amounts of data, with the flexibility and fuzzy parameters characteristic of fuzzy systems, which is important for building cognitive agents for decision-making in complex conditions (Fig. 5) [5]. It also provides more accurate modeling of DMPs, which considers both numerical and fuzzy data, allowing us to achieve optimal results in conditions of uncertainty and a changing environment. Combining these two approaches opens up new opportunities for creating adaptive systems capable of self-improvement and effective integration with other intelligent technologies.

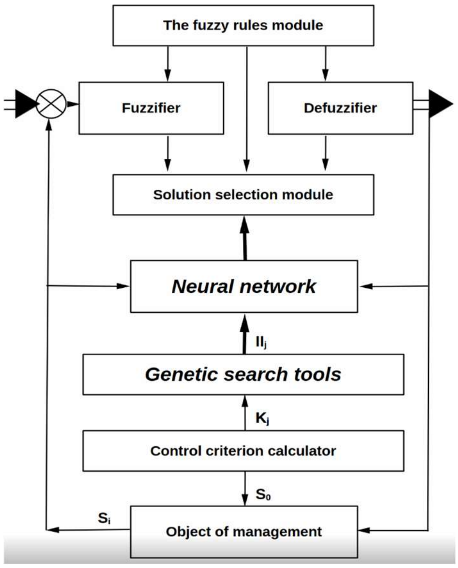

Figure 5: Architecture of an adaptive neuro-fuzzy network

The model optimizes the NNM through a genetic algorithm, combining expert knowledge and objective data to automate the learning process and parameter tuning [15]. Within the framework of this model, linguistic rules are formed, and fuzzy parameters are determined, which are subject to refinement based on the data obtained. NN M acts as an adaptive network with a fixed structure and variable parameters that are optimized through the use of a genetic algorithm, which allows the system to be effectively adapted to changing conditions and provides more accurate results in the context of cognitive decision-making with the integration of AI. The Euclidean distance between the predicted estimates is used to determine the effectiveness of the NNM. y_{pred} and real estimates y_{real}. This approach allows us to measure the degree of approximation of the predicted results to the real ones, which is vital for assessing the model's accuracy and further improving its parameters within the framework of a cognitive decision-making system with the integration of AI. Euclidean distance allows us to measure the discrepancy between the model results and the actual data, which is the basis for optimizing the parameters of the NMM using appropriate algorithms

$$D = \sqrt{\sum_{i=1}^{n} (y_{\text{pred},i} - y_{\text{real},i})^2}, \tag{12}$$

where n is the number of estimation parameters, $y_{\text{pred},i}$ is the predicted value, $y_{\text{real},i}$ is the real value [12].

A genetic algorithm is used to optimize the parameters of the neural network θ, trying to minimize the loss function $L(\theta)$, which determines the model's efficiency. The optimization process consists of finding such parameter values that minimize this loss function, which improves the accuracy and overall efficiency of the neural network in the context of cognitive decision-making [15]

$$\theta^* = \arg\min_{\theta} L(\theta), \tag{13}$$

where θ^* are the optimal parameters that minimize the loss function, which the difference between the predicted and actual values can determine. The loss function can be expressed as the difference between the model's predictions and the actual results, which allows us to assess the effectiveness of the cognitive agent in the DMP. Minimizing this function is a key step in training cognitive agents, as it will enable us to tune the model in such a way as to achieve the most accurate predictions and ensure correct decision-making under different conditions. Therefore, the optimal parameters θ^* provide the best match between theoretical predictions and real data, which increases the effectiveness of integrated AI systems

$$L(\theta) = \sum_{i=1}^{n} (y_{\text{pred},i} - y_{\text{real},i})^2. \tag{14}$$

The optimization process using a genetic algorithm is implemented through several stages, each contributing to achieving an effective result. First, the population is initialized, during which a set of random solutions is created, representing chromosomes for the initial evaluation of the system parameters [2]. Initial options are formed at this stage, which will be evaluated in further optimization. The next step is the selection, during which each of the solutions is assessed using the objective function $L(\theta)$, which allows us to weed out less effective options and choose the best solutions for further optimization. After that, the operations of the data mixing process and random parameter changes are applied, which consist of combining and modifying the characteristics of the best solutions to generate new options with improved properties. The data mixing process allows combining the properties of several solutions, and random changes add an element of stochasticity to avoid local minima and find new optimal options. The evaluation of new solutions allows us to check the effectiveness of the updated parameters and select the best ones for further optimization. This process is repeated through several iterations, including evaluating the current solution, generating new options, and choosing the best solutions for the next stage. Thanks to this approach, the genetic algorithm allows us to adjust the parameters of neural networks effectively, ensuring optimal results when solving the optimization problem, including adaptation to changing conditions and increasing productivity in DMPs [5, 12].

Modifying the architecture of neural-fuzzy systems of the cognitive processing module is carried out by introducing additional adaptive parameters, such as cognitive images, which allows their significance at the level of cognitive perception to be taken into account [14]. Fuzzy models, represented through images, provide formalization and manipulation of symbols without the need to refer to their content, which allows us to work with abstract concepts effectively. At the same time, neural networks, built as graphs, can serve as the basis for interpreting these symbols through the prism of a cognitive image, thus providing flexibility and ambiguity in information processing. Such an approach, which integrates expert knowledge in the form of cognitive images, allows us to implement learning through images, which significantly increases the system's adaptability to changes in the external environment and internal parameters of the technical system. Due to such an integration approach, the cognitive neuro-fuzzy cognitive processing module can respond more accurately to complex and dynamic conditions, ensuring effective management of technical processes in real-time [6, 8, 9].

The processes of adaptation of cognitive systems to changes in external conditions and variations in parameters are implemented through the use of genetic mechanisms that optimize populations of objects and solutions at the level of symbolic and figurative thinking. This approach ensures the dynamic flexibility of systems that respond to changes in the environment, integrating both classical neural network models that reflect the "input-output" relationship and semantic networks that detail the relationships between objects, which allows the modeling of complex objects in the context of management systems. The development of the M-automata and networks concept involves integrating the figurative thinking of MSA into the "control object—control system" circuit, which is implemented through semantic M-networks. These networks are static models that reflect the relationships between objects, which allows the creation of more accurate and adaptive models for management in changing parameters and the environment (Fig. 6) [4, 10, 15, 18]. Such integration allows us to maintain the integrity of the model while simultaneously adapting to changes and ensures more effective decision-making in complex management systems.

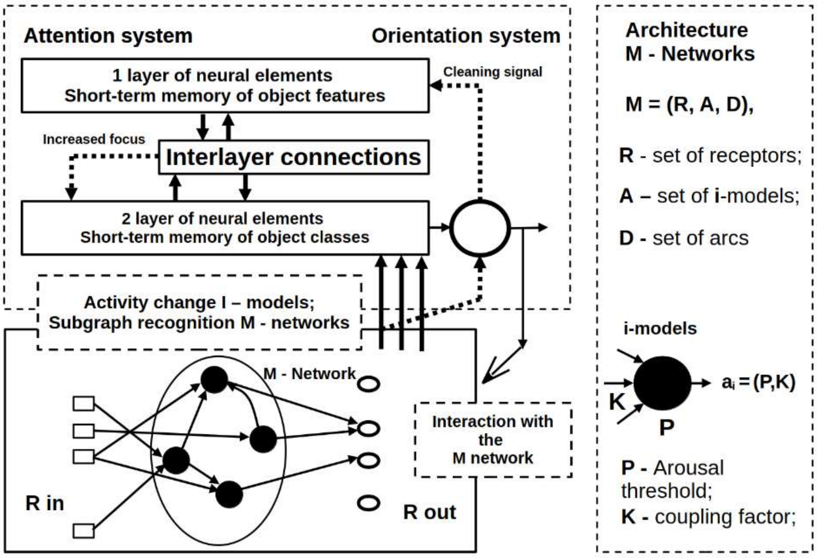

Figure 6: Semantic M-network based on adaptive resonance theories for modeling cognitive processes

Such a model, built in the form of a semantic graph, reflects a neural network's cognitive learning process, which is significantly different from traditional learning using training samples. The key stages of cognitive learning are two main procedures: first, the formation of a set of objects and determining their significance, and second, the establishment of relationships between these objects by assigning connection weights, which resembles the learning process of classical neural networks, but at a new level of cognitive thinking [2, 3, 7].

In such a model, each object of the M-network corresponds to a fuzzy concept, which is determined through expert assessments expressed in the values of synapse weights and threshold values for i-models. This allows us to consider the M-network model as a neural network in essence, and a fuzzy system—in terms of its functioning process. The output layer of the model performs the function of an aggregator and defuzzifier, generalizing the fuzzy information coming from neurons, and transforming it into a more transparent and more interpretable value. The parameters of the middle layer neurons are fuzzy concepts, the membership function of which is determined through the "boost-inhibition" system that controls the process of excitation of i-models: if the excitation of an element exceeds a particular parameter or the excitation of other components, the threshold of this element decreases [9–11]. As a result of such interaction, the semantic graph of the M-network takes the form of a subgraph with increased excitation of vertices and connections between them. Visualizing the significance of each i-model's excitation through digital values, color, or other visual methods allows for the creation of a cognitive graph image that allows for the manipulation of the meaning of symbols, where vertices correspond to objects and the connections between them determine the relationships that exist in the cognitive space. This allows the MSA to adapt to changes in the information environment flexibly, assessing the significance of each object and connection within the given parameters [13].

The "amplification-inhibition" system, acting on the neural M-network, provides the MSA's most active cognitive information, allowing it to change and adapt to changing conditions dynamically. Each stage of this interaction allows the MSA to take into account information at the conscious or subconscious levels, which contributes to assessing the situation and making appropriate decisions and actions. Visual analysis of the cognitive graph, which reflects information interactions between system elements, allows us to flexibly manage the details of viewing this graph, adapting it to the specific goals set by the MSA and individual characteristics of perception and processing of information. This allows the MSA to consider current events and future prospects, predicting actions that may be most optimal in conditions of different scenarios [19–22]. Analysis of MSA activities using a genetic algorithm, which allows adaptation and optimization of strategies, closely connects MSA actions with an AI system, which helps to create more integrated models for real-time decision-making. Thus, the proposed model establishes the possibility of combining subjective and objective knowledge, including declarative knowledge describing facts and procedural knowledge determining actions and strategies. The extended genetic algorithm model with complex factors takes into account multiple aspects influencing decision-making, allowing to carry out highly accurate adaptation in conditions of complex and changing information environments [19]

$$P_{\text{new}} = \sum_{i=1}^{n} \alpha_i \cdot f(P_{\text{old}}, W_i, \delta_i, \epsilon_i) + \beta_i \cdot \int_{0}^{t_{\max}} \sigma(P_{\text{old}}, \eta_i, \tau_i) dt, \tag{15}$$

where P_{new} is the new optimal solution, P_{old} is the current solution, α_i is the coefficient for each population (corresponding to adaptation), $f(P_{\text{old}}, W_i, \delta_i, \epsilon_i)$ is an adaptation function with additional parameters, W_i is a set of weights for each iteration, δ_i are parameters affecting adaptation, ϵ_i is stochastic variations for random parameter changes, β_i is the coefficient for weighting the data mixing process, $\int_0^{t_{\max}} \sigma(P_{\text{old}}, \eta_i, \tau_i) dt$ is the time integral for stochastic parameter changes, η_i is adaptation rate coefficient, τ_i is the time constant for the mutation process.

In the neural network model with the integration of semantic structures, which is aimed at implementing cognitive agents for decision-making in complex information and intellectual systems, the use of nonlinear activation functions, feedback, and a multi-level structure allows for the creation of dynamic connections between objects that take into account the contextual features of each layer of the network, while ensuring more accurate and adaptive information processing under conditions of uncertainty. This integration is achieved through the use of feedback mechanisms, which not only contribute to the dynamic updating of weights in neural connections based on the analysis of input data and their semantic characteristics but also allow to increase the network's ability to model multidimensional dependencies between objects, which significantly expands its functionality in conditions of changing environmental parameters [2, 5, 15]. Such an approach, which takes into account the multilayer architecture of neural networks in combination with semantic networks, allows for the implementation of complex decision-making algorithms in which contextual information enrichment plays a key role in ensuring a high level of cognitive analysis, integrating the advantages of AI with the properties of natural thinking

$$y_j = \sum_{i=1}^{m} \left[\omega_{ij} \cdot \sigma(\sum_{k=1}^{p} \omega_{ik} \cdot x_k + b_i) \right] + \theta_j. \tag{16}$$

In the model of cognitive agents that integrate neural networks with AI mechanisms to support decision-making in complex information systems, the output signal y_j for a neuron j is determined by the sum of the weight coefficients ω_{ij}, that establishes the connection between the neurons of the ith layer and the j^{th} layer, $\sigma()$ is a nonlinear activation function (for example, in the form of a sigmoid or ReLU), x_k is the input signal from the k^{th} neuron from the previous layer, b_i is the bias parameter for the neuron i, θ_j is an additional parameter that provides flexibility for the final bias.

Taking into account feedback between layers, which is implemented through the weight update mechanism ω_{ij}, allows the model to adapt to changing input conditions in real-time, and the differentiation of weight coefficient types ensures the network's ability to take into account the contextual features of multi-level data, increasing the efficiency of cognitive analysis. This approach contributes to the formation of more accurate decision-making models in which the interaction between neurons in different layers of the network reflects complex logical dependencies, which is important for applications in computer science fields, in particular in information systems and technologies, where the accuracy and adaptability of models are key to solving problems with a high degree of uncertainty

$$\Delta\omega_{ij} = \eta \cdot \delta_j \cdot x_i + \gamma \cdot \sum_{k=1}^{m} \theta_k \cdot \omega_{ik}, \tag{17}$$

where $\Delta\omega_{ij}$ is the weight change between neurons in two layers, η is the learning coefficient, δ_j is the error of neuron j in the current layer, γ is the coefficient that considers the feedback effect for changes in neural networks.

The cognitive graph model developed to support decision-making with the integration of AI considers the significance of objects and their relationships in a dynamic information environment. Each object in the graph is characterized by a fuzzy value that adaptively changes depending on the current stage of information processing. Such values reflect the degree of relevance of the object to the problem being solved at each stage of the analysis, which ensures flexibility and accuracy of the cognitive process. Interactions between objects are modeled through the weight coefficients of connections, which are adjusted by changes in system parameters. This allows the cognitive graph to effectively adapt to changes in environmental conditions, maintaining coherence and relevance during decision-making. This approach contributes to the creation of highly efficient information and intellectual systems capable of self-learning and optimization in real-time, which is critically important in modern computer science and technology

$$G_{\text{cog}} = \sum_{i=1}^{n} \alpha_i \cdot f_{\text{activation}}(x_i, \delta_i) + \beta_i \cdot g_{\text{interaction}}(x_i, \omega_i, \tau_i). \tag{18}$$

As part of the development of models and technologies of cognitive agents for decision-making with the integration of AI, it is proposed to use a cognitive graph G_{cog} that describes interactions between system objects. The key elements of this model are: G_{cog} is a cognitive graph that reflects interactions between objects, $f_{\text{activation}}(x_i, \delta_i)$ is an activation function which determines the activity level of each object based on its input parameters x_i and the fuzzy activity coefficient δ_i, $g_{\text{interaction}}(x_i, \omega_i, \tau_i)$ is the interaction function, which models the influence of each object on others through interaction parameters $\omega_i$and time τ_i, α_i and β_i are weighting coefficients that consider shifts in interaction and activation parameters, ensuring the model's adaptability to environmental changes. This structure allows us to reflect complex relationships between objects in a cognitive system and optimize DMPs by dynamically adjusting the activity and interaction between components. Integrating such mechanisms into information systems ensures their increased adaptability, resilience, and ability to self-learn.

The mechanism of tuning classical neural networks for the correction of parameters of a cognitive neural network allows one to model the behavior of an object without the need to take into account its internal semantics. The formation of such a model is based on cognitive compression of information about the object through training a neural network based on a relevant training sample [1, 2]. The training task is divided into two key stages: determining a relevant training sample by analyzing the relationships between the control object and the control system and tuning the cognitive neural network using the specified samples [5, 12, 19]. The process of tuning the parameters of a cognitive neural network involves pre-testing and taking into account subjective aspects of the DMP. The semantic graph of the M-network, which describes a certain scenario, includes object vertices (i-models) that reflect mental and intentional characteristics, such as emotional states. This approach provides the possibility of interactive interaction with the cognitive neuro-fuzzy model, contributing to the accurate assessment of the state of the DMP and considering its cognitive and emotional factors in the DMP.

The study presents a hybrid neural model combining M-networks and adaptive resonance theories (ART-networks), which is focused on integrating natural and AI in the process of cognitive image analysis. Within this model, the Grossberg network performs the function of an artificial cognitive analyzer, providing data clustering through iterative adjustment of weights. The clustering algorithm is constructed in such a way that the first input vector X_1 sets the sample for forming the first cluster. All subsequent vectors are compared with this sample using a defined metric based on calculating the distance between the vectors. A new cluster is automatically created if the deviation exceeds a given threshold. This approach allows the model to adapt to dynamic changes in the input data, preserving the stability of clusters that have already been formed and, at the same time, maintaining plasticity for the detection of new clusters. Due to this, the hybrid model provides a high level of accuracy of cognitive analysis and efficiency in complex information systems, facilitating decision-making even in conditions of incomplete or unclear information [6, 4, 17, 21, 22]

$$d(X_i, X_j) = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2}, \tag{19}$$

where X_i and X_j are the input data vectors, x_{ik} and x_{jk} are their coordinates.

In the process, each input vector belongs to a specific cluster if the condition is met:

$$d(X_i, C_j) \leq \theta, \tag{20}$$

where θ is the vigilance parameter, C_j is the cluster center. If the condition is not met, a new cluster is created, the center of which is defined as $C_{new} = X_i$.

The ART network (Adaptive Resonance Theory) provides stability and plasticity of data clustering processes due to adaptive adjustment of weights, allowing the system to preserve existing clusters and dynamically create new ones in a changing information environment. This approach contributes to the effective integration of cognitive models and AI technologies, allowing decision-making systems to adapt to new conditions and ensure the accuracy of data processing in complex information systems. The equation describes the adaptive updating of weights in the network:

$$\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \eta \cdot \left(x_{ij} - \omega_{ij}^{(t)}\right), \tag{21}$$

where ω_{ij} are the neuron weights, η is the learning coefficient, x_{ij} is the input signal. The algorithm of the ART network includes several key stages: initialization of direct and feedback connections, input vector assignment X, and calculation of neuron activity

$$\alpha_J = \sum_{i=1}^{n} x_i \cdot \omega_{ij}. \tag{22}$$

Neuron selection

$$j^* = \arg\max_j \alpha_i, \tag{23}$$

where $d(X, C_j) \leq \theta$ is running, and the input image can be assigned to an existing cluster. Otherwise, a new cluster must be created. The proposed model allows the implementation of cognitive representation of information through adaptive weight changes and dynamic development of a semantic graph, which corresponds to the principles of mental activity of the MSA [1, 20–22].

Evolutionary procedures for forming neural networks combined with the mechanisms of "boost-inhibition" of M-networks provide a significant advantage, allowing the detection of previously unknown information in a certain image space about which the MSA user had no idea. Such an ability opens up new prospects for learning and self-learning, which are key AI systems and natural intelligence (NI) processes. In addition, this ability serves as an important criterion for assessing the quality of image space selection, ensuring increased efficiency of cognitive agents in decision-making [5, 10, 14. 19, 24].

The mechanism of weight adaptation in a neural network can be described through a loss function $L(\omega)$ that is minimized during training. In updating the weights at the next iteration, $t + 1$ the formula is used:

$$\omega_{t+1} = \omega_t - \eta \nabla_\omega L(\omega_t), \tag{24}$$

where ω_t is the vector of weights at iteration t, η is the learning rate, $\nabla_\omega L(\omega_t)$ is the gradient of the loss function by weights. The degree of correspondence of abstract images created in the process of self-learning to real images can indicate the correctness of the choice of the abstract space model. This approach allows us to visualize the processes of cognitive analysis. It significantly contributes to the development of control systems focused on cognitive learning in the context of models and technologies of cognitive agents for decision-making. The integration of AI with cognitive agents opens up new horizons for solving complex problems, where automated decision-making systems can learn and adapt in real-time, which allows us to improve the interaction between humans and AI significantly. This, in turn, contributes to better adaptation of systems to changing environmental conditions, optimizing the accuracy and speed of decision-making in various areas of activity [3, 19, 25].

Visualization tools, such as the "joint activity bulletin board," effectively manage the classification and selection of similarity categories. This contributes to integrating bionic principles of AI systems with cognitive models of information systems, ensuring productive interaction between AI and NI to achieve common goals in the DMP. This approach allows us to optimize management processes in complex information environments, ensuring the accuracy and speed of decision-making (Fig. 7). The integration of cognitive neuro-fuzzy models into the decision-making support process makes it possible to take into account the multiplicity and uncertainty of input data, which increases the adaptability of the system in a changing environment. Visualization of decision-making results in real-time makes it easier to interpret complex situations and ensures a high level of interaction between users and intelligent systems.

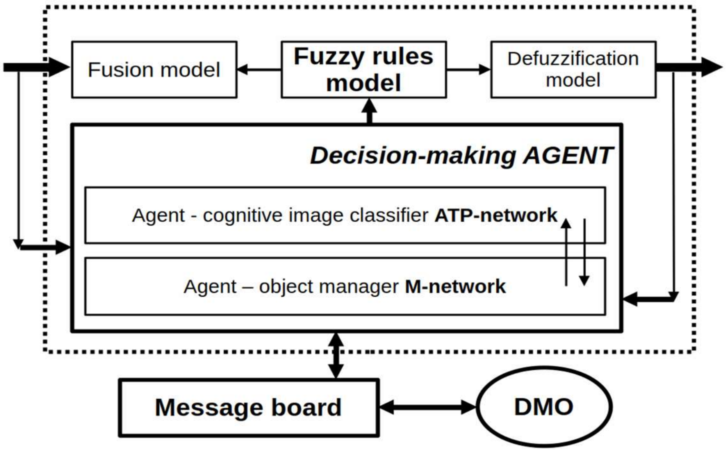

Figure 7: Cognitive neuro-fuzzy model for decision support

Model of cognitive analysis of image space [2, 9]:

$$S(A,B) = \frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} a_i^2}\sqrt{\sum_{i=1}^{n} b_i^2}}, \tag{25}$$

where $S(A,B)$ is the diagonal similarity between the feature vectors A and B, a_i, b_i are the components of the corresponding vectors. The clustering process in a boost-inhibition system (*M*-network), where each input vector x_k belongs to an existing cluster C_j, if

$$\left\| x_{k-}\mu_j \right\| \leq \theta, \tag{26}$$

where μ_j is the cluster center C_j, θ is the threshold value, $\|\cdot\|$ is the selected metric (for example, Euclidean distance). If the condition is not met, a new cluster is created with the center $\mu_k = x_k$.

Attention can be formalized through weight coefficients a_i that reflect the importance of each element of the vector:

$$A(x) = \sum_{i=1}^{n} a_i x_i, \tag{27}$$

where $A(x)$ is the level of attention to the input vector x, the weights a_i are adjusted based on feedback from the MSA. For joint training of natural and AI, a correction mechanism is used

$$\omega_{t+1} = \omega_t + \gamma(\Delta\omega_{\text{artificial}} + \Delta\omega_{\text{natural}}), \tag{28}$$

where γ is integration coefficient x, $\Delta\omega_{artificial}$ is weight change based on AI data, $\Delta\omega_{natural}$ is weight change based on the cognitive model of NI. Formulas demonstrate the interaction between cognitive agents, neural network training, and clustering processes necessary for decision-making [6, 8].

A formula that takes into account the effectiveness of AI and NI in the DMP

$$E_{\text{total}} = \alpha \cdot E_{AI} + \beta \cdot E_{NI}, \tag{29}$$

where E_{total} is the overall efficiency of the cognitive agent, E_{AI} is the efficiency of AI (based on machine learning models, neural networks, etc.), E_{NI} is the efficiency of NI (depends on the cognitive characteristics of a person), α, β are weighting factors that determine the contribution of each type of intelligence to the overall result [14, 15].

The algorithm for forming the best solution within the framework of models and technologies of cognitive agents for decision-making with the integration of AI is based on the integration of AI and NI data. This means that the DMP considers the contribution of each intelligence source—both artificial and natural—to determine the optimal result. The algorithm uses a probabilistic approach, which allows for a more accurate and adaptive solution, integrating the computational capabilities of AI with the cognitive features of human thinking, which is critically important for the practical solution of complex tasks in real conditions

$$R_{\text{optimal}} = \arg\max_{R_i} \left(P_{AI}(R_i) + P_{NI}(R_i) \right), \tag{30}$$

where R_{optimal} is the optimal solution, R_i is the set of possible solutions, $P_{AI}(R_i)$ is the probability of the correctness of the solution R_i proposed by AI, $P_{NI}(R_i)$ is the probability of the correctness of the solution R_i estimated by NI.

The proposed algorithms generalize the approach to building cognitive agents that, by integrating the advantages of AI and NI, provide more efficient and adaptive decision-making in complex information systems. Such synergy allows systems not only to take into account a large number of variables but also to adapt to new conditions, providing a cognitively balanced approach to solving problems that require accuracy, flexibility, and computational power. As a result, these algorithms contribute to optimizing DMPs in real conditions where traditional methods may not be effective enough.

Conclusion

Models and technologies of cognitive agents for decision-making with the integration of AI constitute a new direction that combines the capabilities of neural networks and fuzzy systems to create intelligent solutions that can consider human cognitive characteristics and effectively process information using AI algorithms. Modern research actively uses the agent-oriented paradigm, which allows the creation of models of "joint activity," focusing on the integration of human cognitive capabilities and the computing power of AI, which increases the efficiency of decision-making.

One of the important achievements in this direction is the development of neuro-fuzzy models of cognitive agents, which allow the adaptation of neural network algorithms to work with fuzzy data and provide high flexibility and accuracy in complex situations. These models combine the advantages of neural networks and fuzzy systems, using the principle of functional equivalence, which allows for preserving the best characteristics of each technology and ensuring efficiency in decision-making even in complex conditions of uncertainty.

The development of tools for evolutionary technologies for synthesizing and optimizing cognitive neuro-fuzzy models significantly expands the possibilities of their application in real conditions since these systems integrate knowledge in the form of images and learn based on semiotic modeling. This allows us to combine different levels of information perception—from abstract to figurative—for accurate and effective decision-making. In particular, using such approaches enables us to create more adaptive and intelligent systems that not only process data but also interpret them, taking into account the cognitive characteristics of the user. This ensures flexibility in decision-making and adaptation to new conditions and situations, which makes these systems critical for solving complex tasks in the field of AI. Combining cognitive agents with AI mechanisms allows us to create systems that optimize the DMP, integrating an analytical approach with the intuitive perception of information by the user. This ensures the formation of highly accurate and adaptive solutions in the face of modern challenges.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

References

[1] H. Han, Z. Li, L. Li, R. Zhang, A Structural Expansion Method of Fuzzy Cognitive Map under Cognitive Limitations, in: Int. Conf. on Machine Learning, Cloud Computing and Intelligent Mining, MLCCIM, 2022, 146–154. doi:10.1109/MLCCIM55934.2022.00031

[2] B. Sahoh, K. Haruehansapong, M. Kliangkhlao, Causal Artificial Intelligence for High-Stakes Decisions: The Design and Development of a Causal Machine Learning Model, IEEE Access 10 (2022) 24327–24339. doi:10.1109/ACCESS.2022.3155118

[3] G. Klein, Sources of Power: How People Make Decisions, MIT Press, 2017. doi:10.1061/(ASCE)1532-6748(2001)1:1(21)

[4] D. Nallaperuma, et al., Online Incremental Machine Learning Platform for Big Data-Driven Smart Traffic Management, IEEE Transactions on Intelligent Transportation System 20(12) (2019) 4679–4690. Doi: 10.1109/TITS.2019.2924883

[5] G. Hinton, R. Salakhutdinov, Reducing the Dimensionality of Data with Neural Networks, Science 313 (2006) 504–507. doi:10.1126/science.112764

[6] B. Igoche, O. Matthew, P. Bednar, A. Gegov, Leveraging Structural Causal Models for Bias Detection and Feature Adjustment in Machine Learning Predictions, in: IEEE 12th Int. Conf. on Intelligent Systems, IS, 2024, 1–7. doi:10.1109/IS61756.2024.10705239

[7] J. Pearl, The New Science of Cause and Effect, with Reflections on Data Science and Artificial Intelligence, in: IEEE Int. Conf. on Big Data, Big Data, 2019. doi:10.1109/BigData47090.2019.9005644
[8] W. Tang, Y. Wang, Intelligent Method for Solving Optimal Control of Discrete Stochastic Dynamic Systems with Probability Criterion, in: IEEE Int. Symposium on Intelligent Control, 2003, 959–962. doi:10.1109/ISIC.2003.1254766
[9] Y. Smitiukh, Y. Samoilenko, Y. Kostiuk, O. Kryvoruchko, K. Stepashkina, Development of a Prototype of an Intelligent System for Predicting the Quality of Dairy Manufacture, IEEE Intelligent Systems (2022). doi:10.1109/IS57118.2022.10019699
[10] S. S. Kafila, S. Mittal, V. L. V, M. Lourens, M. Soni, Combining AI with Machine Learning to Improve Decision-Making in New Business Technologies, in: Int. Conf. on Trends in Quantum Computing and Emerging Business Technologies, 2024, 1–5. doi:10.1109/TQCEBT59414.2024.10545201
[11] J. Pearl, D. Mackenzie, The Book of Why: The New Science of Cause and Effect, Penguin Books, 2018, 47–54. doi:10.56645/jmde.v14i31.507
[12] M. Usman, V. Muthukkumarasamy, X. Wu, Mobile Agent-based Cross-Layer Anomaly Detection in Smart Home Sensor Networks using Fuzzy Logic, IEEE Transactions on Consumer Electronics 61(2) (2015) 197–205. doi:10.1109/TCE.2015.7150594
[13] Y. Kostiuk, O. Kryvoruchko, M. Tsiutsiura, A. Yerukaiev, N. Rusan, Research of Methods of Control and Management of the Quality of Butter on the Basis of the Neural Network, in: Smart Information Systems and Technologies, SIST, 2022 106–110. doi:10.1109/SIST54437.2022.9945764
[14] T. Hovorushchenko, O. Pavlova, M. Bodnar, Development of an Intelligent Agent for Analysis of Nonfunctional Characteristics in Specifications of Software Requirements. Eastern-European J. of Enterprise Technologies 1(2) (2019) 6–17. doi:10.15587/1729-4061.2019.154074
[15] L. Yu, S. Wang, K. K. Lai, An Intelligent-Agent-based Fuzzy Group Decision making Model for Financial Multi-criteria Decision Support: The Case of Credit Scoring, European J. of Operational Research 195 (3) (2011) 942–959. doi:10.1016/j.ejor.2007.11.025
[16] Y. X. Zhong, A Cognitive Approach to Artificial Intelligence Research, in: 5th IEEE Int. Conf. on Cognitive Informatics, 2006, 90–100. doi:10.1109/COGINF.2006.365682
[17] V. Lytvyn, V. Vysotska, D. Dosyn, O. Lozynska, O. Oborska, Methods of Building Intelligent Decision Support Systems based on Adaptive Ontology, in: IEEE 2nd Int. Conf. on Data Stream Mining & Processing, DSMP, 2018, 145–150. doi:10.1109/DSMP.2018.8478500
[18] O. Kryvoruchko, Y. Kostiuk, A. Desyatko, R. Zakharov, R. Brzhanov, Analysis of Technical Indicators of Efficiency and Quality of Intelligent Systems, J. of Theoretical and Applied Information Technology 101(24) (2023) 127–8139.
[19] Y. Kostiuk, O. Kryvoruchko, A. Desyatko, Y. Samoilenko, K. Stepashkina, R. Zakharov, Information and Intelligent Forecasting Systems based on the Methods of Neural Network Theory, in: Smart Information Systems and Technologies, SIST, 2023, 168–173. doi:10.1109/SIST58284.2023.10223499
[20] S. Russell, P. Norvig, Artificial Intelligence: A Modern Approach, 3rd ed., A Simon & Schuster Company Englewood Cliffs, New Jersey, 2015.
[21] T. Pomorova, T. Hovorushchenko, Artificial Neural Network for Software Quality Evaluation based on the Metric Analysis, in: IEEE East-West Design & Test Symposium, EWDTS, 2013, 200–203. doi:10.1109/EWDTS.2013.6673193
[22] Y. Kostiuk, O. Kryvoruchko, A. Desiatko, R. Zakharov, Development of a Decision Support System in a Higher Education Institution using Project-Oriented and Competence-based Approaches, Science and Technology Today J. 4(32) (2024) 1048–1068.
[23] I. Tyshyk, H. Hulak, Testing an Organization's Information System for Unauthorized Access, in: Cybersecurity Providing in Information and Telecommunication Systems, vol. 3826, 2024, 17–29.
[24] V. Lakhno, V. Malyukov, N. Mazur, L. Kuzmenko, B. Akhmetov, V. Hrebeniuk, Development of a Model for Decision Support Systems to Control the Process of Investing in Information Technologies. Eastern-European J. of Enterprise Technologies 3(103) (2020) 74–81. doi:10.15587/1729-4061.2020.194531
[25] D. Berestov, O. Kurchenko, Y. Shcheblanin, N. Korshun, T. Opryshko, Analysis of Features and Prospects of Application of Dynamic Iterative Assessment of Information Security Risks, in: Cybersecurity Providing in Information and Telecommunication Systems, CPITS, 2021, 329–335.