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Method for constructing a cognitive map of processes in a dynamic system using the cooperation of large language models

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Abstract. In the context of growing demands for rapid decision-making and in-depth analysis of complex dynamic systems – particularly when available data are limited and the involvement of experienced experts is either impractical or prohibitively expensive – the development of new methods for the construction of the model becomes especially relevant. The use of large language models (LLMs) as expert systems offers significant reductions in resource expenditure and accelerates the modelling of complex technical, environmental, and socio-economic systems. This study aimed to investigate and demonstrate the potential and capabilities of LLMs as expert systems in constructing cognitive maps. The article proposes and substantiates an architecture for the cooperation of LLM ensembles to formally generate vertices-variables and weight coefficients in cognitive maps, thereby enabling the automation of the modelling process without the involvement of human experts. A typical prompt for an LLM was decomposed into structural components: context description (D), model role instruction (R), instruction (I), conditions (C), and response format (F). A method for determining these components through expert-based analysis is proposed. A prompt system was developed to enable structured data processing and the identification of interrelationships among system elements. The practical effectiveness of the approach was demonstrated using a case study on forecasting water quality in the Sabarivske Reservoir near Vinnytsia. For most physicochemical indicators, the modelling showed low error rates (2.09-4.6%), even with a minimal amount of input data. The proposed method is promising for modelling and forecasting tasks in complex systems with limited data availability, particularly in environmental, socio-economic, and engineering contexts, where the speed of obtaining reliable results is critical for informed decision-making

Keywords: LLM; generative artificial intelligence; intelligent technology; systems analysis; modelling; forecasting; dynamic system

Introduction

To address forecasting and decision support tasks, it is crucial to possess a model capable of predicting a system's reaction to certain perturbations. As is known, if a system is well-defined, it is typically modelled using mathematical methods. Conversely, if a system exhibits high uncertainty and a significant volume of data, data science and intelligent models are generally applied. In the case of weakly structured systems with a limited amount of data, an expert approach and intelligent formalisation methods based on cognitive maps are employed. A cognitive map (CM) is a directed graph that connects vertices-variables by arcs with weights, whose values are constant and lie within the range . Cognitive maps are an effective tool for modelling dynamic systems; however, traditional approaches to CM construction rely on expert evaluations and require considerable time. Furthermore, they are susceptible to

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expert subjectivity, which complicates the development of stable models. Simultaneously, modern large language models (LLMs) already contain a wide spectrum of expert knowledge and can significantly accelerate this process, provided their cooperation is correctly organised and an effective prompting system is in place. This underscores the necessity for developing a method utilising LLMs to automate the construction of cognitive maps.

Over recent years, several studies have been published concerning the use of large language models and cognitive maps for modelling complex systems. However, each of these illuminates somewhat different aspects of this issue and does not offer a comprehensive solution for the full automation of CM construction based on LLMs. For instance, T. Liu *et al*. (2024) demonstrated the capability of LLMs (using the LLaMA 2 model as an example) to perform forecasting of the dynamics of various systems without additional training. Their conclusion posited that LLMs can effectively serve as a basis for predictive models, even for complex dynamic processes. Researchers R. Schuerkamp *et al*. (2025) proposed an original mechanism for integrating multiple expert cognitive maps using LLMs. Their method of automatic "reconciliation" of contradictory statements enables LLMs to analyse causal relationships independently generated by several experts and to propose a single, agreed-upon map without explicit conflicts. While this opens up the prospect of large-scale integration of heterogeneous knowledge in complex tasks, it is based on maps previously formulated by experts rather than on full automation.

In the research by A. Feleki *et al*. (2023), an integrated Deep FCM approach was applied, where a convolutional neural network (CNN) was combined with fuzzy cognitive maps (FCMs) for the diagnosis of heart diseases. However, the LLM (GPT-3.5) was only used for the automatic generation of text explanations in natural language. In practice, this allowed for the analysis of medical images using a convolutional neural network and their combination with clinical data in an FCM classifier with enhanced explanatory capability. In the study by W. Godoy *et al.* (2024), the level of student satisfaction with factors such as teaching quality, infrastructure, and social environment, among others, was compared, with results obtained using an LLM and results modelled using a CM that was constructed traditionally. The results were found to be almost identical: a score of 7.5 was obtained using the CM, and a score of 7.4 was obtained using OpenAI's GPT-4 LLM. However, the cognitive map itself was created separately by expert means, without any attempts at its automatic generation using an LLM.

As for the use of cognitive maps (CMs) themselves in modelling tasks, this approach is demonstrating increasing popularity within the scientific community due to its ability to effectively represent complex causal relationships across various subject domains, whilst providing an intuitively understandable visualisation of system dynamics and supporting decision-making under uncertainty. Specifically, O. Saliieva & Y. Yaremchuk (2020) proved the reliability of modelling the impact of threats on the security level of an information protection system and a critical infrastructure object, conducted based on a cognitive approach. Similarly, S. Shevchenko *et al.* (2024) demonstrated the effectiveness of cognitive maps for modelling information security risk scenarios. CMs in their research enable the identification of key vulnerabilities and optimal enterprise protection strategies through scenario analysis. However, the map itself was constructed manually based on expert experience, and the issue of automated formation of the structure and weighting coefficients using LLMs was not considered.

An analysis of the systemic risks associated with the application of chatbots in education is presented in the study by O. Cherniuk (2023). The author utilised a cognitive map to investigate the interaction between students and generative language models, identifying both positive consequences (such as increased motivation and access to knowledge) and threats (for instance, the temptation to violate academic integrity). In this study, the cognitive map was also constructed manually by experts, and the use of LLMs for automation was not considered.

Another relevant example of implementing cognitive maps is presented in the article by V. Mokin *et al.* (2021), where the authors proposed a mathematically grounded method for synthesising a stable multi-connected CM by sequentially expanding the base map to higher orders. This approach demonstrated its effectiveness through the analysis of ecological processes in the Southern Bug River in the Vinnytsia Region. However, in this case, as well, the identification of vertices and interconnections was based on prior expert input, meaning that full automation without specialist involvement was not envisaged.

Based on the analysis conducted, several aspects can be identified which are either not addressed at all or are insufficiently covered in current scientific literature: the development of a completely automated method for constructing cognitive maps without manual expert involvement; the use of LLMs not merely for explanations or reconciling existing maps, but for generating the entire structure of the CM (vertices-variables and weighting coefficients); and the evaluation of the actual effectiveness of such an approach for complex systems with limited data. Consequently, this article aimed at the development of a method for constructing a cognitive map of processes in a dynamic system using the cooperation of large language models in the role of experts. Specifically, this entailed defining the key elements of the system, their interrelationships and the cognitive map's weighting coefficients, as well as forming a system of prompts to ensure effective LLM cooperation, followed by verifying the adequacy and accuracy of the constructed model using real data.

Materials and Methods

Complex dynamic systems in discrete time $k=0, 1, 2, \ldots$, can typically be formalised in the form of sets of values for input variables U, state variables X, and an output variable Y. A case was considered where in each modelling scenario, there is only one input and only one output variable. It is necessary for the values of the variables to be represented on a single scale (e.g., normalised), as the use of different units of measurement can lead to inaccuracies in modelling. Importantly, the graph is undirected and all variables are interchangeable; that is, an output variable or some intermediate state variable can become an input and vice versa, the main point is to always adhere to the requirement that there is only one input and one output variable in each instance. The methodology for constructing cognitive maps posits that all system variables are represented as vertices of a graph, and the interrelationships between them as arcs with weights that characterise the strength of influence (Roberts, 1976; Romanenko & Miliavskyi, 2023). Thus, a cognitive map is a formalised tool for modelling and analysing complex dynamic systems. Each value of the output variable can be calculated using the expression:

$$Y[k] = F(X[k-i], U[k-i]), i = \overline{1, d}, \tag{1}$$

where $F(\cdot)$ is the system model that links input variables to state variables and state variables to output variables, and d is the diameter of the graph, i.e., the length of the longest path between the input and output vertices. A signal propagates from the input vertex to the output vertex. Over one time step k, it moves from one vertex to another. Therefore, from the most distant vertex, it reaches the output in d steps, but from some vertices, the signal may arrive sooner. For a CM to be stable, the absolute values of all eigenvalues of the adjacency matrix must be less than 1 (Mokin *et al*, 2021).

The greater the number of vertices in a CM, the more patterns it accounts for, but the more difficult it is to ensure its stability. In conducting this research, the results of the articles by V. Mokin *et al.* (2020, 2021) were considered, in an attempt was made to synthesise guaranteed stable CMs mathematically. However, such CMs possess a rather simplified (somewhat degenerate) structure, which significantly reduces the set of complex systems for which they would be adequate. Conversely, if a CM has many vertices and a complex structure, it is more adequate for the processes within the system, taking into account features that correspond to external influences upon it. Thus, the main criterion for CM optimisation is finding a compromise between the number of vertices, to ensure maximum adequacy, and ensuring its stability, so that it can be used for tasks such as modelling, scenario-based data forecasting, and supporting optimal decision-making. In this context, LLMs can become an effective tool for solving CM optimisation problems. Specifically, LLMs are capable of automating CM construction by analysing textual and numerical data. Thanks to their ability to work with large volumes of data and account for complex hidden patterns, LLMs can help to achieve a compromise between the model's adequacy and its stability.

The proposed method is based on decomposing the task of forming a CM into a series of subtasks, which are solved using the cooperation of LLMs. This decomposition allows the overall problem to be broken down into individual steps: identification of variables (CM vertices), data preparation and generalisation, construction of CM weighting coefficients, and subsequent integration of the obtained results. Thus, to address the stated problem, an algorithm was developed for the method of constructing a cognitive map of processes in a dynamic system using the cooperation of large language models:

1. Identification of the main vertices-variables of the cognitive map using an ensemble of LLM M_{LLM1}, which most fully characterise the complex system being modelled and, simultaneously, are best supported by data for expert analysis.

2. Transformation of data for a given output value $Y[k]$ (corresponding numerical values from the sets of input variables U, state variables X, and the output variable; a textual description of the general characteristics of the object and each of its components that can be identified within it based on various criteria; a textual description of the current stage of the object's functioning, etc.) using an ensemble of LLM M_{LLM2} into a natural language textual description Ω.

3. Estimation of the upper bound of values for each indicator using an ensemble of LLM M_{LLM3} for subsequent use during the normalisation of indicator values.

4. Generating the weights of the cognitive map using the values of Ω and the LLM ensemble M_{LLM4}, taking into account typical constraints on these values in the range [−1, 1] and ensuring its stability.

5. Checking the cognitive map for stability. If the CM is stable, the problem is solved; otherwise, revert to stages 1, 2, 3, or 4 and repeat them with different parameters (e.g., change the "temperature" parameter, which in LLMs is responsible for the diversity of the output, or similar).

This algorithm ensured the decomposition described above and the utilisation of the advantages of large language model cooperation at each stage of cognitive map formation. Breaking down the task into a sequence of prompts, instead of using a single complex query, significantly reduced the requirements for the context volume and capabilities of the LLMs, allowing for the creation of more detailed and structurally complex cognitive models. Furthermore, the cooperation of LLMs facilitated the combination of the strengths of different neural network architectures to achieve a synergistic effect.

Testing of the proposed method was conducted using real data on the water quality in the Sabarivske Reservoir on the Southern Bug River near Vinnytsia. The data were obtained from the Vinnytsia City Open Data Portal and included average monthly values of water quality indicators (Vinnytsia City Council, 2024). The CM generated using the developed method was evaluated for stability and forecasting accuracy.

Results and Discussion

Designing the architecture for the cooperation of large language models

Common methods for combining multiple LLMs can be divided into two categories. Direct model merging – for instance, parameter merging, which involves combining several LLMs into one by aggregating their parameters (model weights), for example, through averaging. A key requirement here is that the model architectures must be compatible (Akiba *et al.*, 2025). The second method is the combination of input and output data between models (cooperation of LLMs), which includes ensemble methods (LLM ensemble) or other, more general cooperation techniques. Ensemble methods involve combining texts generated by multiple LLMs to improve the quality of the response and can occur either directly during generation or after the text has been fully generated (Cao *et al.*, 2024; Lu *et al.*, 2024).

The second method is, in general, more promising as it offers flexibility and does not require full compatibility with model architectures. Furthermore, cooperation-based approaches allow for a more effective combination of the strengths of different LLMs, which can significantly enhance the overall response quality without the need to modify the models themselves. Therefore, the use of ensemble methods (LLM ensemble) has been proposed.

The proposed architecture for the cooperation of large language models is based on the principles of ensemble methods in machine learning and collective decision-making. The theoretical foundation of this approach is the concept of "the wisdom of crowds", which suggests that aggregating independent evaluations often leads to more accurate results than individual assessments (Schoenegger *et al.*, 2024). In the context of LLMs, this concept is implemented through the parallel or sequential application of models, followed by the reconciliation of their outputs. To ensure the reliability of results and reduce the risk of "hallucinations" by the models, an architecture with result validation is applied, where the outputs of multiple LLMs are compared and reconciled by a dedicated reconciliation model.

In general, the nature and complexity of each ensemble depend on the specifics of the task. To minimise the typical "hallucinations" of LLMs and improve the reliability of results, it is suggested to use at least several LLMs to generate intermediate results, which are then summarised by another LLM (Fig. 1) (Das & Srihari, 2024). The presence of "hallucinations" in LLMs is a known issue, as the models can generate false or incorrect information, which may nonetheless appear plausible, making it difficult to detect and verify (Huang *et al.*, 2025). One possible reason for this may be that LLMs operate based on statistical patterns and lack a "true understanding" of the text (Bender & Koller, 2020; Bender *et al.*, 2021). In certain cases, some sub-tasks (for example, data conversion to another format) can be performed by individual LLMs without involving an ensemble or even algorithmically – for instance, S.-W. Chen & H.-J. Hsu (2023) demonstrated that integrating an external numerical module significantly reduces numerical hallucinations in Mistral 7B, improving the accuracy of mathematical calculations.

Figure 1 illustrates the structure of a large language model ensemble, where the input prompt P undergoes parallel processing through k independent LLMs (M_1, M_2,..., M_k). Each prompt is initially transformed by pre-processing operators φ_1, φ_2,..., φ_k, which can adapt the query to the specifics of the respective model. Inference parameters ψ_1, ψ_2,..., ψ_k define the configuration of each model (temperature, top_p, etc.). The results from all models are collected by operator T, undergo post-processing φ_{k+1}, and are fed into the coordinating model M_{k+1} with its own parameters φ_{k+1}, which forms the final result Y based on all the data received.

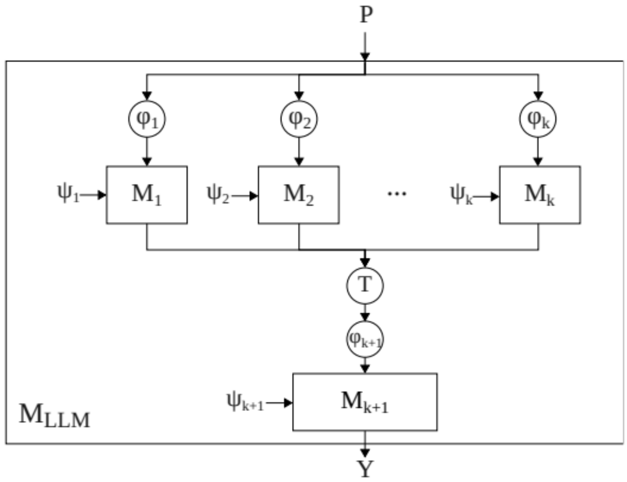

Figure 1. Example of LLM ensemble with parallel prompt processing using k LLM M_1, M_2,..., M_k and subsequent combination of results by a coordinating model M_{k+1}
Source: authors' development

The following set of models was defined: $\Lambda = \{M_1, M_2,..., M_n\}$, where each model M_i maps the prompt P to the response space R_i of model M_i: $M_i : \{P\} \to R_i$. If a single prompt P is simultaneously fed as input to all elements of a subset of models $\{M_1, M_2,..., M_k\} \subseteq \Lambda$, a set of results $Y^{Parallel}$ from the parallel processing of the prompt by the LLM ensemble will be obtained:

$$\left\{Y_1^{\text{Parallel}}, Y_2^{\text{Parallel}}, \dots, Y_k^{\text{Parallel}}\right\} = \left[M_1^{\psi_1}, M_2^{\psi_2}, \dots, , M_k^{\psi_k}\right](P), \quad (2)$$

where ψ_i are the inference parameters of model M_i.

When considering an ordered set $\{M_1, M_2,..., M_k\} \subseteq \Lambda$, where the prompt was fed as input to model M_1, and the response of each model was passed to the next in order within the set, the result $Y^{\text{Sequential}}$ of sequential prompt processing by the LLM ensemble was obtained:

$$Y^{Sequential} = M_k^{\psi_k}\left(M_{k-1}^{\psi_{k-1}}\left(\dots M_1^{\psi_1}(P)\right)\right) =$$
$$= \left(M_k^{\psi_k} \circ M_{k-1}^{\psi_{k-1}} \circ \dots \circ M_1^{\psi_1}\right)(P). \quad (3)$$

When combining the parallel (2) and sequential (3) approaches to prompt processing, a method was applied where the prompt was first fed simultaneously to the input of a subset of models $\{M_1, M_2,..., M_k\} \subseteq \Lambda$. Subsequently, the obtained responses from the models, $Y^{Parallel}$, were used as input data for the next sequence of models $\{M_{k+1}, M_{k+2},..., M_m\} \subseteq \Lambda$ for further processing:

$$Y = \left(M_m^{\psi_m} \circ \varphi_m \circ M_{m-1}^{\psi_{m-1}} \circ \varphi_{m-1} \circ \dots \circ M_{k+1}^{\psi_{k+1}} \circ \varphi_{k+1}\right) \times \times\left(T\left(\left[M_1^{\psi_1} \circ \varphi_1, M_2^{\psi_2} \circ \varphi_2, \dots, M_k^{\psi_k} \circ \varphi_k\right](P)\right)\right), \quad (4)$$

where $T: R_1 \times R_2 \times \dots R_k \to P$ is the function for transforming the results of parallel processing into a new prompt, and $\varphi_i:\{P\} \to \{P\}$ is the prompt pre-processing operator before feeding it to the input of the model. For the implementation of the proposed method, four types of LLM ensembles are required: M_{LLM1}, M_{LLM2}, M_{LLM3}, M_{LLM4}, where each of the ensembles can be represented as:

$$M_{LLM_i}(P) = F_i\left(\left(M_m^{\psi_m} \circ \varphi_m \circ M_{m-1}^{\psi_{m-1}} \circ \varphi_{m-1} \circ \dots \circ M_{k+1}^{\psi_{k+1}} \circ \varphi_{k+1}\right) \times \times\left(T\left(\left[M_1^{\psi_1} \circ \varphi_1, M_2^{\psi_2} \circ \varphi_2, \dots, M_k^{\psi_k} \circ \varphi_k\right](P)\right)\right)\right). \quad (5)$$

As noted above, the M_{LLM1} ensemble was responsible for analysing the input textual description of the system and identifying the key elements (vertices of the cognitive map). The M_{LLM2} ensemble is intended for generalisation and conversion of heterogeneous data into a textual description , suitable for further processing. The M_{LLM3} ensemble is designated for analysing the available data regarding the system's state and determining the value limits for the CM vertices. This is necessary to normalise the values of the variables and bring them to a single scale. The M_{LLM4} ensemble determined the nature and intensity of influence between system elements based on the available textual descriptions, which allows for the formation of the CM weights.

For all four ensembles $\{M_{LLM1}, M_{LLM2}, M_{LLM3}, M_{LLM4}\}$, a common set of models L was used, and the ensemble architecture involved the parallel generation of results with their subsequent reconciliation by a coordinating model. The set L included: GPT-4o (OpenAI), Claude Sonnet 3.5 (Anthropic) – general multimodal large language models, Gemini 1.5 Flash (Google) – a model with high context processing performance, GPT-1o preview (OpenAI) – a model trained in a particular manner that demonstrates higher efficiency in solving complex tasks. The GPT-1o preview model was used as the coordinating model.

Development of a prompt system for LLM ensembles

To implement the idea proposed above, a system of prompts was developed that allows for the effective utilisation of LLMs in constructing a cognitive map. This process includes the processing of available data regarding the system being modelled, the selection of indicators based on which the CM will be built, the calculation of influence weights between indicators, the calculation of indicator limits for normalising state vectors in the CM, and the interaction between LLMs. The use of a systematic approach to creating these prompts enabled all aspects of the cognitive map construction process to be taken into account.

It is known that the effectiveness of LLM responses increases if the prompt explicitly sets the "role" that the LLM is to "perform" (Kong *et al.*, 2024; Wang *et al.*, 2024). This functions as setting a context that limits the semantic space for generating responses. Therefore, it is proposed that each developed prompt begins with a sentence that explicitly defines the role. Each prompt can be decomposed into constituent parts and represented as a tuple:

$$P = (D, R, I(D), C, F), \quad (6)$$

where D is the task context in terms of the subject domain, R is the role instruction for the LLM, $I(D)$ is instructions regarding data processing, C is additional conditions and constraints, and F is instructions regarding the response format.

D ("Data") – the domain context, which contains data relevant to the task (e.g., a textual description of the system state, observation JSON data, etc.). The domain context should provide the LLM with sufficient information for decision-making and may consist of several independent parts, for instance: D_E – a list of elements of the system being modelled, D_1, D_2, D_3 – evaluations from three independent experts that need to be generalised, and so forth. The structured presentation of data is justified by the need for a clear distribution of information blocks to avoid confusion and ensure flexibility in adaptation to different scenarios.

R ("Role") – the "role" instruction for the LLM (e.g., "You are an expert in assessing water quality in river basins"). Such a role assignment sets a specific context for the prompt and helps to obtain more specialised responses. The use of role instructions allows the LLM to adapt the style, terminology, and depth of the generated text according to the chosen area of expertise.

$I(D)$ ("Instructions") – instructions on precisely what needs to be done with the data. The instructions should be precise, understandable, and detailed. Correctly formulated instructions ensure a more accurate generation result. The more detailed the expected actions are described, the lower the probability of obtaining an incorrect interpretation or a result that does not meet expectations.

C ("Constraints") – additional conditions, formal limitations, and clarifications. Additional conditions are introduced to prevent the LLM from deviating beyond the defined semantic and contextual space. Constraints help to reduce the risk of obtaining incorrect results and also ensure compliance with practical requirements.

F ("Format") – instructions regarding the response format. Clear requirements for the response format are justified by the necessity for automated subsequent processing, integration with other tools, or verification of results. The absence of a formalised format would complicate the application of the generated data in real-world scenarios, reducing the overall effectiveness of the method.

This formalisation ensured a structured approach to prompt construction, which, in turn, enhanced the manageability and transparency of the result generation process. Without such a clear structure, prompts could be inconsistent, overly complex, or insufficiently formalised, which would lower the quality of the generated CMs and their practical applicability. Furthermore, the formalised approach simplifies the process of debugging and optimising prompts, as it allows for a systematic analysis of the influence of individual components on the final generation result and enables targeted changes to improve the quality of the output.

Example application of the method for forecasting surface water quality

The proposed method was applied in practice using real data. The Vinnytsia City Open Data Portal provides average monthly values for water quality indicators in the Sabarivske Reservoir on the Southern Bug River, upstream of the drinking water intake for Vinnytsia Vodokanal (Vinnytsia City Council, 2024). Significantly more data are available on the water intake itself, but these are not published. Public data are primarily needed by the city authorities and population for using the Sabarivske Reservoir for recreational purposes, fishing, and so forth. However, for these purposes, knowledge of future values is more valuable than retrospective ones. To implement the described approach, the ensembles for solving this problem were defined as follows:

The set L is common to all four ensembles: L = (GPT-4o, Claude Sonnet 3.5, Gemini 1.5 Flash, GPT-1o preview). The architecture of the ensembles is analogous to that shown in Figure 1. A query to the ensemble indicated that for solving the problem of forecasting the ecological state and water quality indicators in the river, significantly more indicators measured at different points upstream and downstream with greater regularity are needed, along with information about water discharge, hydrological parameters of the river (flow velocity, sinuosity, roughness of the channel bed, turbulent diffusion coefficient), meteorological conditions (precipitation, temperature, atmospheric pressure), and so forth. Such data are absent in this dataset, and the available data are very limited (one data point, averaging interval – one month, information on hydrological and meteorological parameters is absent, information on hydrobiological indicators is absent). Therefore, it is impossible to identify either a mathematical or an intelligent model. However, building a cognitive map is, theoretically, possible. Taking expert knowledge of the research objects into account suggests that the best period for modelling with the available data is the winter season, as during this time, the impact of biotic indicators on the ecological condition of the water is minimal, and physical-chemical characteristics (temperature, oxygen concentration) are predominantly determined by abiotic processes. The LLM GPT-4o was used to formulate this assumption, followed by verification by a human expert. According to the algorithm of the proposed method, a textual description of the water state in January 2024 was generated using the ensemble. Subsequently, this description was used in prompts as the structural element D from formula (6). An example prompt is shown in Figure 2.

Prompt	
You are an expert in assessing water quality in river basins.	R
From the provided textual description of the water state in the river section and the list of indicators, determine the degree of influence of the indicator "dissolved oxygen concentration (mg/L)" on the rest of the indicators	I
The degree of influence of an indicator on each other indicator must be expressed numerically within the range of –1 to 1, and the absolute value of the sum of all influences must be less than 1	C_1
The sign of the influence should reflect how the indicator changes under the influence of "dissolved oxygen level (mg/L)": if with an increase in "dissolved oxygen level (mg/L)", the indicator increases, then the sign of the influence should be positive. If with an increase in "dissolved oxygen level (mg/L)", the indicator decreases, then the sign of the influence should be negative	C_2
D1 <description> D1 </description>	D_1
D2 <list of indicators> D2 </list of indicators>	D_2

Provide the final answer at the end in JSON format
{
"Dissolved oxygen level (mg/L)": {
"Indicator": influence
}
}
	F

Figure 2. Prompt $P_{weights} = (D_1, D_2, R, I, C_1, C_2, F)$ for generating relationships between indicators
Source: authors' development

According to the developed method, a cognitive map was generated, depicted in Figure 3. It reflects five key water quality indicators: biological oxygen demand, temperature, ammonium salt, dissolved oxygen, and total iron, as well as their interrelationships. These indicators were selected for modelling using the LLM ensemble. They are minimally sufficient for identifying certain patterns regarding water status, and it is for these indicators that the most data are available on the Vinnytsia City Council portal (Vinnytsia City Council, 2024). The weighting coefficients of the relationships between them were generated according to the proposed method.

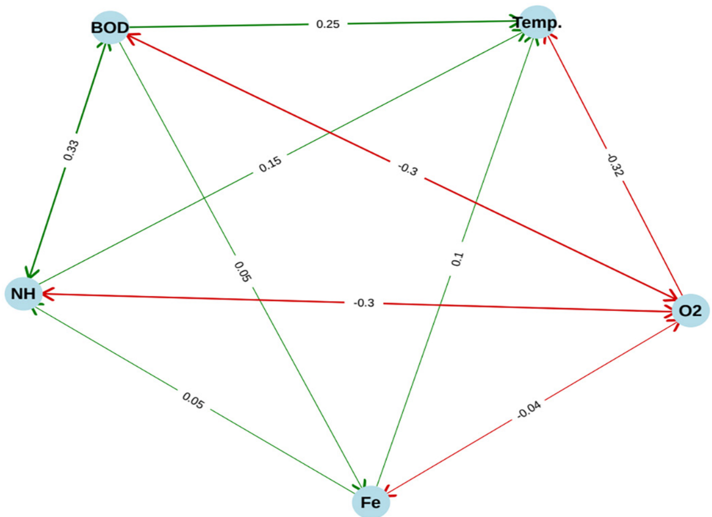

Figure 3. Generated cognitive map of water quality indicators in the Southern Bug River near Vinnytsia for the winter period

Note: BOD – biochemical oxygen demand; Temp – temperature; NH – ammonium salt (NH4+); O2 – dissolved oxygen; Fe – total iron. Green lines indicate a positive influence, where an increase in one indicator leads to an increase in another; red lines indicate a negative influence, where an increase in one indicator causes a decrease in another. Numerical values on the arcs reflect the strength of the mutual influence of the indicators in the range from −1 to 1, where larger absolute values indicate a stronger relationship between the indicators

Source: authors' development

Based on the obtained CM, cognitive modelling of a temperature change scenario for the following month, February 2024, was performed. To verify the reliability of the forecast, the modelling results were compared with the actual temperature and water quality indicators for February 2024. The obtained results are presented in Table 1.

Table 1. Comparison of modelling results with actual water quality indicators

Indicator	Actual value	Model prediction	Relative modelling error (%)
Dissolved oxygen concentration	9.5 mgO_2/dm^3	9.125 mgO_2/dm^3	3.95%
Ammonium salt (NH4+)	0.43 mg/dm^3	0.421 mg/dm^3	2.09%
BOD (biochemical oxygen demand)	6.3 mgO_2/dm^3	6.01 mgO_2/dm^3	4.6%
Total iron	0.35 mg/dm^3	0.6 mg/dm^3	71.4%

Source: authors' development

As can be seen from the table, three out of the four indicators were modelled with high accuracy. This indicates the effectiveness of the applied method in forecasting the main physicochemical parameters of water. However, for the "Total iron" indicator, the relative error was 71.4%. Such a significant discrepancy may be due to additional factors that were not taken into account in the modelling. This suggests that for this indicator, the aforementioned assumption regarding the greater adequacy of the model for the winter period is not significant. This is quite expected, as the concentration of iron in water is considerably less related to the activity of aquatic organisms than other indicators of the ecological state of the water.

Based on the generated cognitive maps, which were produced by the LLM ensemble, there is partial overlap with the results of R. Schuerkamp *et al.* (2025). In their experiment, ChatGPT successfully merged several expert maps into one; in the present study, the LLM ensemble managed to integrate disparate fragments of knowledge from text into a coherent map. This integration process proved particularly effective for complex systems where the interrelationships between components are not always immediately obvious. The use of a model ensemble allowed for a more balanced representation of knowledge and helped to avoid the potential biases of individual models. Thus, the findings support the idea that LLMs can act as knowledge integrators, forming a cognitive model of a system from potentially conflicting statements derived from expert cognitive maps. Simultaneously, this research goes further by employing LLMs to construct the map from scratch, rather than merely merging existing maps.

Compared to the approach of A. Feleki *et al.* (2023), where GPT-3.5 generated textual explanations for an already existing FCM, the method described in this study effectively does the opposite – it generates the FCM itself.

Instead of requiring the black box to explain its decisions in human language, the black box is "compelled" to explain the problem in the language of causal relationship graphs. This "inverted" approach has made it possible to obtain a model that is more interpretable from the outset. This is particularly important in the context of increasing demands for the transparency of algorithmic solutions and the necessity to explain not just individual conclusions, but also the general logic of the model's reasoning. Furthermore, such an approach potentially reduces the time required for creating cognitive maps and makes this tool more accessible to researchers without deep expertise in modelling complex systems.

In the context of dynamic systems, it is worth comparing the obtained results with those of T. Liu *et al*. (2024). That research demonstrated the ability of LLMs to forecast time series, effectively imitating the system dynamics through a sequence. The proposed method, however, aims for an explicit representation of dynamics via a graph of influences, which makes it more transparent and interpretable for end-users. In this research, attention was focused on the structure of interrelationships between the system components, rather than solely on their behaviour over time. It can be noted that the model constructed by the LLM in the conducted study successfully reproduced the qualitative structure of the system (the set of influences between variables). This allowed not only for forecasting changes in the system but also for understanding the causes of these changes and potential levers of influence. Thus, this complemented the results of T. Liu *et al*. (2024), as LLMs can not only predict behaviour but also reveal the structure of interrelationships, which significantly expands the analytical toolkit for working with complex systems in various subject domains.

Compared with Ukrainian studies, it can be stated that the solution presented in this research fills an important gap. In the article by S. Shevchenko *et al*. (2024), experts manually modelled cybersecurity risks via FCMs. Similarly, in the study by O. Cherniuk (2023), a map of the impact of chatbots on education was constructed based on expert analysis. The proposed method, in contrast, allows for the automation of such steps: instead of manual map construction, it is sufficient to provide the LLM with a full description of the problem. This significantly accelerates the modelling process and makes it less dependent on the availability of specific experts. Moreover, the automated approach may prove less susceptible to individual expert biases, especially if an ensemble of different LLMs is utilised. At the same time, the proposed method does not exclude expert contribution but rather shifts it to the level of validation and correction of automatically generated models, which optimises the use of valuable expert time and knowledge.

Conclusions

The article addresses the issue of using LLMs as experts for constructing cognitive maps of complex dynamic systems. The research goal, which was to develop a method for constructing a cognitive map of processes in a dynamic system using the cooperation of large language models in the role of experts, has been successfully achieved. The proposed method allows the automation of the cognitive map construction process without the involvement of human experts and requires only a minimal set of input data.

In the course of the study, the architecture for the cooperation of LLM ensembles was proposed and substantiated for the formal generation of vertices-variables and weight coefficients in cognitive maps. The decomposition of a typical prompt into structural components was carried out, and approaches for their definition were suggested. A system of prompts was developed to ensure structured data processing and the identification of relationships between system elements. The practical effectiveness of the approach was demonstrated through the example of predicting water quality in the Sabarivske Reservoir, where modelling for three of the four physicochemical indicators (dissolved oxygen concentration, ammonium salt, and biological oxygen demand) showed a small error (2%-5%), even with a minimal amount of input data.

The proposed method holds significant importance for the applied modelling of complex systems, as it allows for the rapid creation of formalised models in situations where traditional approaches face limitations due to a lack of data or experts. The developed formal system of prompts helps to improve the accuracy of LLM responses, thanks to its structured nature and the use of known techniques for enhancing the quality of the generated text. Utilising ensembles of different LLMs instead of a single model helps to minimise potential biases and "hallucinations", which is critically important when modelling real-world systems. For one of the four physicochemical indicators ("Total iron"), the method showed a significant error, indicating the necessity of considering additional factors for specific system variables. This confirms that cognitive maps constructed with the assistance of LLMs require validation and potential adjustment for specific variables or relationships.

Promising directions for future research include expanding the LLM cooperation architecture to work with multimodal data, improving methods for ensuring the stability of generated cognitive maps and developing approaches for the automatic correction of cognitive maps based on feedback from real data. Separate attention is needed to investigate the effectiveness of the proposed method in other subject domains, particularly for complex technical, ecological, and socio-economic systems.

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Conflict of Interest

None.

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Метод побудови когнітивної карти процесів у динамічній системі із використанням кооперації великих мовних моделей

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Анотація. В умовах постійного зростання вимог до швидкого прийняття рішень і глибокого аналізу складних динамічних систем, коли доступні дані обмежені, а залучення досвідчених експертів часто є неможливим або занадто витратним, розроблення нових методів побудови моделей набуває особливої актуальності. Використання великих мовних моделей (LLM) як експертних систем дозволяє суттєво знизити ресурсні витрати та прискорити процес моделювання складних технічних, екологічних та соціально-економічних систем. Метою даної роботи було дослідження та практична демонстрація потенціалу та можливостей LLM, як експертних систем, у процесі побудови когнітивних карт. У даній роботі запропоновано та обґрунтовано архітектуру кооперації ансамблів LLM для формалізованого генерування вершин-змінних та вагових коефіцієнтів когнітивних карт, що дозволяє автоматизувати процес моделювання без залучення експертів-людей. Здійснено декомпозицію типового промпта (вказівки) до LLM на структурні складові: опис контексту (D), рольову настанову моделі (R), інструкцію (I), умови (C) та формат відповіді (F) та запропоновано підхід їх визначення експертним шляхом. Розроблено систему таких промптів, яка забезпечує структуроване оброблення даних та ідентифікацію взаємозв'язків між елементами системи. Практичну ефективність підходу продемонстровано на прикладі прогнозування стану води у Сабарівському водосховищі біля м. Вінниця, де для більшості фізико-хімічних показників моделювання продемонструвало малу похибку (2.09–4.60 %) навіть за мінімального обсягу вхідних даних. Запропонований метод є перспективним для задач моделювання та прогнозування у складних системах з обмеженим обсягом даних, зокрема в екологічних, соціально-економічних та інженерних сферах, де швидкість отримання надійних результатів має критичне значення для прийняття обґрунтованих рішень

Ключові слова: ВММ; генеративний штучний інтелект; інтелектуальна технологія; системний аналіз; моделювання; прогнозування; динамічна система