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# PROJECT-ORIENTED METHODOLOGY FOR PROACTIVE EPIDEMIC MANAGEMENT BASED ON ARTIFICIAL INTELLIGENCE AND SEIRS MODELS

The subject of the research presented in the article is the processes of proactive epidemic management as complex socio-medical systems under conditions of high uncertainty, limited resources, and dynamic external influences, including the use of mathematical epidemiological modeling and intelligent digital technologies. The purpose of the study is to develop a project-oriented methodology for epidemic management based on the integration of the classical SEIRS model with artificial intelligence, machine learning, and digital decision-support systems, enabling a transition from reactive response to proactive forecasting and prevention of infectious disease outbreaks. The following tasks are addressed in the article: the formation of a conceptual and process-based model of proactive epidemic management within a project-oriented approach; the development of an integrated architecture for the collection, analysis, and interpretation of epidemiological data; the adaptation of the SEIRS compartmental model to dynamic parameterization using machine learning methods; the justification of geospatial and multi-agent approaches for capturing heterogeneity in disease spread; and the identification of the role of intelligent optimization methods in managing interventions throughout the epidemic project lifecycle. The following methods are used: mathematical modeling of epidemiological processes based on systems of SEIRS differential equations; machine learning and ensemble forecasting methods for dynamic estimation of model parameters; geospatial analysis and multi-agent modeling to represent population mobility and spatial risk patterns; reinforcement learning methods for optimizing management decisions; and project-oriented management approaches for organizing and adapting epidemic response processes. The following results are obtained: principles of proactive epidemic management based on the integration of epidemiological modeling and artificial intelligence are formulated; a project-oriented methodology that aligns the project management cycle with the phases of the SEIRS model is proposed; a generalized structure of a hybrid intelligent model capable of adapting to different types of infectious diseases, including tuberculosis and COVID-19, is developed; and the potential for improving early risk detection and rational resource allocation under crisis conditions is substantiated. Conclusions: the application of the proposed project-oriented methodology and the integrated SEIRS model enhanced with artificial intelligence provides a foundation for the transition to proactive epidemic management, increases the adaptability of public health systems, and can be used as a universal methodological framework for the development of intelligent epidemic forecasting and prevention systems in complex and unstable environments.

**Keywords**: proactive epidemic management; project-oriented methodology; artificial intelligence; SEIRS model; machine learning; digital health; epidemiological forecasting; decision support systems.

## 1. Introduction

Infectious diseases remain one of the key threats to global public health security, despite significant advances in medical technology and epidemiological surveillance systems. The COVID-19 pandemic has demonstrated the limitations of traditional reactive approaches to epidemic management, which are largely focused on responding after outbreaks have been identified, rather than on preventing them. Additional challenges are posed by increasing population mobility, urbanization, socioeconomic inequality, and climate change, which complicate the prediction of the spread of infectious diseases.

For Ukraine, these problems are particularly acute amid prolonged military aggression, which has led to the disruption of the healthcare infrastructure, internal and external population displacement, fragmentation of epidemiological data, and limited access to medical services in a number of regions. Under such conditions, maintaining the effectiveness of traditional surveillance systems and planning anti-epidemic measures is extremely difficult, necessitating the implementation of adaptive, intelligently managed, and proactive approaches to epidemic management.

Traditional epidemic management models are based on retrospective analysis of statistical data and are primarily used to describe existing disease trends. This approach is insufficiently effective in conditions of rapidly changing epidemiological situations, high uncertainty, and incomplete data. Reactive strategies lead to delayed implementation of management interventions, inefficient use of resources, and increased socioeconomic losses.

Proactive epidemic management involves shifting the focus from response to prediction, based on risk forecasting, early detection of potential outbreaks, and advance planning of containment measures. This approach requires the use of mathematical models capable of accounting for the complex dynamics of infectious processes, as well as tools for analyzing large volumes of heterogeneous data in real time.

Artificial intelligence and machine learning methods open up new possibilities for epidemiological forecasting and management. Unlike classical deterministic models, intelligent approaches allow for the adaptive assessment of key parameters of infection spread, taking into account socioeconomic, demographic, spatial, and behavioral factors. The integration of digital medical records, geospatial data, population mobility indicators, and clinical trial results forms the basis for building comprehensive management decision-support systems.

Of particular importance in this context are extended compartmental models, notably the SEIRS model, which accounts for latent stages of infection and the possibility of recovered individuals reverting to the susceptible group. Combining such models with artificial intelligence methods allows for a shift from static parameterization to a dynamic, context-dependent description of epidemiological processes.

Despite active research in the application of artificial intelligence in epidemiology, most existing studies focus on specific aspects of disease incidence forecasting or diagnostic automation. The integration of epidemiological modeling with project-oriented approaches to management – which allow for the systematic organization of decision-making, the implementation of interventions, and their adaptation in a dynamic environment – has been studied to a much lesser extent.

Thus, there is a research gap between mathematical models of infection spread and practices for managing epidemics as complex, multi-stage projects implemented under conditions of limited resources and high uncertainty.

The aim of this article is to develop and justify a project-oriented methodology for proactive epidemic management based on the integration of the SEIRS model with artificial intelligence methods and digital technologies.

To achieve this goal, the following tasks are addressed in this work:

– formalize the concept of proactive epidemic management within a project-based approach;

– develop an integrated methodological framework combining epidemiological modeling and intelligent data analysis methods;

– justify the use of dynamic parameterization of the SEIRS model using machine learning; demonstrate the adaptability of the proposed methodology to various types of infectious diseases and crisis conditions.

## 2 Analysis of recent studies and publications

### 2.1. Compartmental models and the development of SEIR/SEIRS approaches

Mathematical modeling of epidemics has its origins in the classical theory proposed by W. Kermack and A. McKendrick, which laid the foundations for the compartmentalization of populations and the formalization of infection and recovery processes [1]. Further development of these ideas led to the emergence of SEIR-type models, which account for the latent (incubation) period of the disease [2].

The SEIRS model, which additionally describes the loss of immunity and the return of recovered individuals to the susceptible group, is widely used for infectious diseases with a long-lasting or inconsistent immune response, particularly tuberculosis and COVID-19 [3]. Studies show that SEIRS models better reproduce the wave dynamics of epidemics and can describe endemic disease states [4].

Further modifications of SEIR/SEIRS models aim to account for time lags, spatial heterogeneity, and various intervention scenarios [5]. Such approaches improve forecasting accuracy but simultaneously complicate parameter calibration and require integration with additional data sources [6].

### 2.2. Artificial intelligence, geospatial, and multi-agent approaches in epidemiology

The growing availability of large datasets on epidemiological, socioeconomic, and mobility data has facilitated the active implementation of artificial intelligence and machine learning methods in infectious disease forecasting [7]. Review studies indicate that ML approaches are capable of identifying hidden nonlinear dependencies inaccessible to classical statistical methods and adapting to changing conditions of infection spread [8].

At the same time, numerous authors highlight the limitations of purely data-driven models, which, without mechanistic interpretation, may lose their generalization ability and be sensitive to changes in context [9]. In this regard, hybrid approaches are being actively developed that combine compartmental models with neural networks, ensemble algorithms, and graph models [10].

Particular attention is paid to the use of graph neural networks and recurrent architectures to account for spatiotemporal dependencies and population mobility [11]. Such models demonstrate increased accuracy in short-term forecasting and can be used to assess the impact of policy interventions [12].

Geospatial models are a key tool for analyzing regional epidemic dynamics, as they allow for the consideration of population migration, transportation links, and local environmental characteristics [13]. Studies show that spatially explicit SEIR models provide a more realistic representation of infection spread compared to aggregated approaches [14].

Multi-agent systems (MAS) complement geospatial models by allowing the description of individual agents' behavior, their contacts, and individual characteristics [15]. Such approaches are particularly effective for modeling infections with long incubation periods and complex social determinants, notably tuberculosis [16].

In previous work, the authors developed geospatial multi-agent models to analyze the transmission of tuberculosis and COVID-19, allowing for the integration of demographic, medical, and spatial factors within a single modeling environment [17–20].

### 2.3. Optimization of management interventions and decision support systems

Proactive epidemic management involves not only forecasting but also selecting optimal intervention strategies under conditions of limited resources. In this context, reinforcement learning methods are being actively researched, enabling the formulation of management policies based on an assessment of the long-term consequences of decisions [21].

Studies demonstrate the effectiveness of RL approaches for optimizing non-pharmaceutical interventions, testing planning, and the allocation of healthcare resources [22]. Other works combine RL with compartmental models and real-world data for adaptive control of the intensity of restrictions at the regional level [23].

Decision support systems integrated with epidemiological models and analytical dashboards are viewed as a key tool for translating forecasts into practical management actions [24]. In previous studies, the authors demonstrated the potential of using intelligent agents to support the management of global threats and complex crisis processes [25].

### 2.4. Summary of the literature review

The conducted literature review indicates that current research covers a wide range of approaches – from classical SEIRS models to hybrid systems based on artificial intelligence, geospatial analysis, and reinforcement learning [26–28]. At the same time, most studies focus on individual components of epidemiological analysis and do not form a comprehensive methodology for managing epidemics as complex projects. Thus, a research gap remains regarding the integration of SEIRS models, intelligent data analysis methods, multi-agent systems, and optimization approaches within a single project-oriented management cycle, which justifies the conduct of this study.

## 3. Purpose and objectives of the study

The aim of this work is to develop a project-oriented methodology for epidemic management based on the integration of the classical SEIRS model with artificial intelligence, machine learning, and digital decision support systems, thereby facilitating a shift from reactive response to proactive forecasting and prevention of infectious disease outbreaks.

The article addresses the following tasks: forming a conceptual and process model of proactive epidemic management within a project-based approach; developing an integrated architecture for the collection, analysis, and interpretation of epidemiological data; adapting the SEIRS compartmental model to the conditions of dynamic parameterization using machine learning methods; justifying the use of geospatial and multi-agent approaches to account for the heterogeneity of infection spread; determining the role of intelligent methods for optimizing management interventions in the project cycle of epidemic response.

## 4. Project-oriented methodology for proactive epidemic management

### 4.1. General architecture of the proposed methodology

The proposed methodology represents a systematic and cyclical approach to project management of processes for forecasting and minimizing epidemic

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risks (Fig. 1). It integrates project management principles (particularly agile and hybrid methodologies) with artificial intelligence and machine learning methods to form an adaptive, data-driven decision support system. The main goal of the methodology is to transform reactive responses to infectious disease outbreaks into proactive risk management based on predictive analytical models.

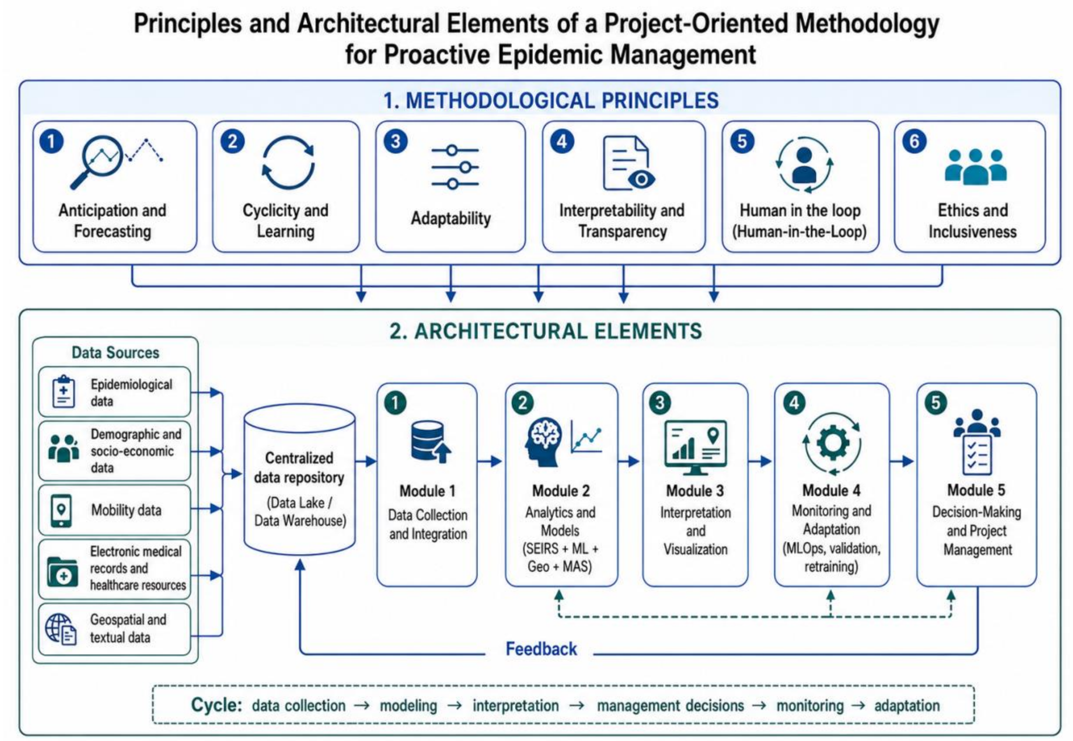


**Fig. 1.** Principles and Architectural Elements of Proactive Epidemic Management Based on SEIRS and AI

In Fig. 1, the proposed methodology is presented in the form of two interrelated levels: the level of methodological principles and the level of architectural elements. The principles level defines the conceptual requirements for building a proactive epidemic management system: anticipatory nature, cyclicality, adaptability, interpretability, expert involvement in the decision-making loop, and ethical use of data and artificial intelligence algorithms. The architectural level reflects the functional structure of the system, which ensures the implementation of these principles. It includes sources of epidemiological, demographic, geospatial, mobile, and medical data; a centralized data repository; modules for information collection and integration; analytics and modeling; interpretation and visualization of results; monitoring and adaptation; as well as a module for supporting management decision-making. Feedback between the modules ensures the cyclical updating of models, the adaptation of forecasts, and the adjustment of management interventions in accordance with changes in the epidemiological situation.

### 4.2. Formalization of the management methodology

Management methodology is defined as a system of principles, models, methods, mechanisms, procedures, and tools that determine the sequence and content of actions for the effective achievement of project or organizational goals.

Formally, the management methodology is presented as a tuple:

$$M_{PEM} = \langle P, M, T, R, C \rangle, \quad (1)$$

where $M_{PEM}$ – project-oriented methodology for proactive epidemic management, $P$ – principles and approaches (*Principles*), $M$ – models, methods, and mechanisms (*Methods*), $T$ – tools and techniques (*Tools*), $R$ – roles and responsibilities (*Roles*), $C$ – cycles and processes (*Cycles*).

Key characteristics define the internal structure of the methodology and the specifics of its practical implementation. They are divided into **structural** and **functional**.

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*Structural characteristics*

Structural characteristics include:

**Conceptual framework** – management philosophy, principles, and strategic guidelines.

**Process model** – stages, phases, and sequences of management actions.

**Toolkit** – methods, techniques, and software tools.

**Success criteria** – metrics and performance evaluation indicators.

The functional characteristics of the methodology include:

**Normativity** – the definition of formalized rules for performing activities.

**Systematic** approach – ensuring the integrity and consistency of the approach.

**Adaptability** – the ability to adjust depending on conditions.

**Reproducibility** – ensuring the stability of results.

Project management methodologies are classified as:

– strategic (high-level);

– tactical (operational);

– integrated (comprehensive).

Based on the degree of flexibility, the following are distinguished:

– rigid (waterfall, cascade);

– flexible (agile, adaptive);

– hybrid methodologies.

The effectiveness of a methodology is evaluated using an integral function:

$$E(M)=\sum_{i=1}^{n} w_i \cdot f_i(P,M,T,R,C,E), \qquad (2)$$

where $E(M)$ – methodology effectiveness; $w_i$ – factor weighting coefficients; $f_i$ – influence functions of individual components; $E$ – external environment.

The methodology must satisfy a set of constraints:

$$M_{\text{feasible}}=\left\{M \mid C_{\text{resource}}(M)\le B, \middle| C_{\text{time}}(M)\le T, \middle| R_{\text{risk}}(M)\le R_{\max}\right\}, \qquad (3)$$

where $B$ – budget constraints; $T$ – time constraints; $R_{\max}$ – acceptable risk level.

Within the scope of this study, the components of management methodology are viewed not as a general classification of management approaches, but as functionally interrelated elements of proactive epidemic management. The conceptual level is defined by the principles of anticipatory action, adaptability, cyclicality, interpretability, expert involvement in the decision-making loop, and ethicality. The process level is implemented through an iterative cycle of data collection, modeling, interpretation, decision-making, monitoring, and adaptation. The instrumental level encompasses SEIRS models, machine learning methods, geospatial analysis, multi-agent modeling, and digital decision support systems. The organizational level is related to defining the roles of public health specialists, data analysts, managers, and stakeholders in the process of implementing anti-epidemic measures.

### 4.3. Iterative phases of predictive epidemic management

The conceptual framework of the methodology is implemented through four main iterative phases that form the "Predictive Epidemic Management Cycle".

**Phase 1.** Data preparation and integration

*Objective*. Collection, cleaning, harmonization, and consolidation of heterogeneous data from distributed sources into a centralized repository.

*Actions*. Identification of sources, automated collection of streaming and static data, NLP text processing, geocoding.

*Result*. Creation of a consolidated, analysis-ready dataset.

**Phase 2.** Analysis, modeling, and forecasting

*Objective*. Identification of patterns, construction and training of predictive models, generation of development scenarios.

*Actions*. Feature engineering, exploratory data analysis (EDA), training and validation of machine learning model ensembles (time series, graph networks), simulation (e.g., agent-based modeling).

*Result*. Predictive indicators (R-number, incidence forecast, spread risk assessment), heat maps, "what-if" scenarios.

**Phase 3.** Interpretation and decision support

*Objective*. To transform technical forecasts into concrete, interpretable recommendations for management decision-making.

*Actions*. Visualization of results (dashboards, GIS maps), ranking and explanation of forecasts (SHAP, LIME), development of intervention options with an assessment of their potential impact.

*Result*. Reports for management, early warning signals, proposals for resource allocation (medicines, doctors, beds).

**Phase 4.** Implementation, monitoring, and adaptation

*Goal*. Implementation of selected measures, real-time assessment of their effectiveness, and model adjustment based on new data.

*Actions*. Integration with supply chain and HR management systems, continuous monitoring of key performance indicators (KPIs), feedback from practitioners, retraining of models. Result. Implemented anti-epidemic measures, updated and improved predictive models, closing the cycle.

### 4.4. Modular architecture and interconnections

The architecture is implemented as five key modules, each of which is responsible for a specific function and interacts with the others through clearly defined APIs and data flows (Table 1).

**Table 1.** *Modular structure of the methodology and interaction between stages*

| Module | Main functions | Technologies/Approaches | Interaction with other modules |
|---|---|---|---|
| 1. Data collection and integration module | Aggregation, cleansing, storage | Apache NiFi/Kafka, Airflow, ETL processes, NLP, APIs | Data source for Module 2. Receives quality feedback from Module 4 |
| 2. Analytics and modeling module | Generation of forecasts and analytical insights | Python (Scikit-learn, TensorFlow/PyTorch, Prophet, libraries for geospatial analysis), graph databases | Consumes data from Module 1. Provides forecasts and insights to Module 3. Receives retraining signals from Module 4 |
| 3. Interpretation and visualization module | | Dash/Streamlit, Tableau, Power BI, GIS platforms (QGIS, ArcGIS), interpretation libraries (SHAP, ELI5) | Receives results from Module 2. Provides an interface and recommendations for users (Module 5) |
| 4. Monitoring and adaptation module | Presenting results, explaining models | MLflow, Evidently AI, automated retraining pipelines, A/B testing | Monitors the productivity of Module 2. Provides quality metrics and data for adaptation. Interacts with Module 5 to assess the impact of decisions |
| 5. Decision-making and project management module | Model validation, performance monitoring, model lifecycle management (MLOps) | Project management systems (Jira, Asana), collaboration and document management platforms | Uses insights from Module 3. Initiates actions, the results of which are returned as data to Module 1 |

The flow is cyclical. For example, a decision made in Module 5 (e.g., quarantine) generates new data (population mobility, reduced incidence), which enters the system via Module 1, is verified by Module 4, and may lead to the recalibration of models in Module 2 and the updating of recommendations in Module 3.

Information flows: the data types, sources, and formats used in the methodology are presented in Table 2.

**Table 2.** *Data types, sources, and presentation formats*

| Data type | Examples of sources | Nature | Output formats | Use in models |
|---|---|---|---|---|
| Epidemiological | Official reports from the Ministry of Health, global statistics (WHO, ECDC) | Structured time series | CSV, JSON, databases (SQL) | Direct training of forecasting models |
| Demographic and socioeconomic | Census data, State Statistics Service data, social indices | Structured, semi-structured | CSV, JSON, geo-JSON | Influencing factors, risk segmentation |
| Mobility data | Anonymous aggregated data from telecommunications providers, Google Mobility, Apple Mobility | Structured time series | CSV, JSON, geospatial formats | |
| Climatic and environmental | Weather services, satellite data | Structured time series, images | NetCDF, GRIB, CSV | Key predictor of spread dynamics |
| Text and news | | Unstructured texts | Text, HTML, PDF | Accounting for seasonal and weather factors |
| Healthcare resource data | News, social media, scientific preprints (medRxiv), official announcements | Structured | Databases (SQL), API | Early warning detection, infodemic monitoring, semantic analysis |
| Genomic data | Registers of hospitals, drug stocks, vaccines, and personnel | Structured biological sequences | FASTA, specific bioinformatics formats | Resource allocation optimization, workload forecasting |

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### 4.5. The methodology's adaptability to different types of infectious diseases

The proposed methodology serves as a universal framework whose parameters can be adapted to specific disease categories at the level of data, models, and management processes, enabling the rapid development of an effective forecasting system for new epidemic threats.

1. Adaptation at the data level

For airborne infections (COVID-19, influenza), data on mobility and indoor population density take center stage.

For zoonoses (Ebola, West Nile fever) – climate data and the ranges of animal carriers.

For infections transmitted through water or food – data on water quality and sanitation.

2. Adaptation at the model level

*R-number and time series*. These are universal, but model parameters (lag, seasonality) are adjusted to the incubation period and dynamics of a specific disease.

*Graph neural networks (GNN).* The graph topology changes: for airborne epidemics – a graph of transportation links between cities; for STIs – a contact graph.

*Agent-based modeling.* Agent behavior rules, infection probability, and immunity parameters are customized to the transmission mechanism and pathogenesis of the disease.

3. Adaptation at the project management level

*Response speed*. For highly contagious diseases with a short incubation period, the "Monitoring-Adaptation" phase cycle is accelerated to a daily basis.

*Critical resources*. For some diseases, the key resources are respirators and mechanical ventilation; for others, they are antidotes or specific vaccines. The decision support module adapts its recommendations accordingly.

*Communication strategy*. The selection of channels and content for informing the public depends on the mode of transmission and the target risk groups.

Thus, the proposed methodology is not a rigid framework but a toolkit that allows for the rapid assembly of an effective predictive management system for any new infectious disease threat, minimizing the time required to develop one from scratch.

Integrating the SEIRS epidemiological model with AI and digitalization can enable proactive forecasting of tuberculosis outbreaks, potentially reducing morbidity by predicting risks in high-burden regions, such as central and southeastern Ukraine.

Principles emphasizing data-driven forecasting, multi-stakeholder collaboration, and the ethical use of AI will help overcome war-related obstacles, although challenges such as access to data in occupied territories may limit effectiveness.

The use of AI for early detection and digital tools for real-time monitoring facilitates sustainable project management in the context of protracted crises, taking into account discussions regarding the accuracy of AI across diverse populations.

The methodology is based on proactive prediction, using AI to forecast and mitigate the spread of tuberculosis before it escalates. Key principles include.

– adaptability to the context of war-torn Ukraine;

– integration of digital health records for a continuous data flow;

– ethical considerations for vulnerable groups, such as displaced persons. Engaging stakeholders – from government health agencies to NGOs – ensures inclusive decision-making with a focus on equity to avoid exacerbating inequalities in regions such as Dnipro and Odesa.

## 5. An extended mathematical SEIRS–AI model: the case of tuberculosis control in Ukraine

### 5.1. Prerequisites for applying the model for tuberculosis in Ukraine

The proposed methodology conceptually aligns the compartments of the SEIRS epidemiological model with the phases of project management. This approach allows for the integration of mathematical modeling of the spread of infectious diseases with management decision-making processes in a digital environment.

Specifically, the correspondence between the SEIRS compartments and the project phases is defined as follows:

**Susceptible** – the planning and risk assessment phase, utilizing artificial intelligence tools for spatial mapping and analysis of risk factors.

**Exposed** – the prevention phase, implemented through digital tools for contact tracing, vaccination, and preventive interventions.

**Infectious** – the rapid response phase using intelligent triage, including CAD systems for medical image analysis.

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**Recovered** – the monitoring, reintegration, and relapse prediction phase using AI.

**Return to Susceptible** – the long-term sustainability phase, which includes educational measures, revaccination, and strategic planning.

Within this framework, artificial intelligence and digitalization serve as the instrumental foundation of the methodology, enabling the analysis of large volumes of data, decision support, and secure information exchange, particularly through the use of blockchain technologies.

Given the current public health challenges in Ukraine – exacerbated by the war since 2022 and prior disruptions to the healthcare system due to the COVID-19 pandemic – the need for proactive management of tuberculosis (TB) control projects is extremely urgent.

The SEIRS epidemiological model is particularly well-suited for analyzing tuberculosis because it accounts for:

– the presence of latent infection;

– temporary immunity;

– the possibility of reinfection after recovery.

Tuberculosis is characterized by a prolonged latent phase, during which individuals may remain infected for years before the disease becomes active. Integrating the SEIRS model into a digital environment supported by artificial intelligence methods enables a shift from reactive to anticipatory management strategies, ensuring early intervention in high-risk scenarios, particularly during mass population displacement and damage to medical infrastructure.

Ukraine remains a country with a high tuberculosis burden, particularly of multidrug-resistant (MDR) forms. Statistical data indicate a complex and unstable epidemiological landscape. During the COVID-19 pandemic, TB incidence temporarily declined (for example, by 31% in 2020), but since 2021, an increase in rates has been observed – by 26% in 2022 and by 7% in 2023.

Central regions of Ukraine, particularly the Dnipropetrovsk and Kirovohrad regions, have experienced a sharp rise in incidence, linked to internal population displacement. Southeastern regions, including the Odesa and Donetsk regions, show consistently high rates, complicated by limited data availability from temporarily occupied territories. A significant increase in cases of MDR-TB has also been recorded among Ukrainian migrants abroad.

Within the proposed methodology, the principles of proactive epidemic management are considered as universal conceptual provisions that can be adapted to a specific infectious disease. For tuberculosis in Ukraine, their application is linked to the disease's prolonged latent phase, the risk of reinfection, regional heterogeneity of the epidemic process, the impact of internal migration, and limitations of the healthcare system under martial law.

In the context of tuberculosis management in Ukraine, these principles are applied as follows:

1. **Anticipation and forecasting** – the use of SEIRS models and artificial intelligence methods to predict the risks of tuberculosis spread before a sharp increase in incidence, particularly in regions with a high disease burden and a significant number of internally displaced persons.

2. **Cyclicality and learning** – organizing management as a continuous cycle of data collection, modeling, interpretation of results, decision-making, monitoring, and model adjustment based on new information.

3. **Adaptability** – the ability to adjust model parameters and management interventions in response to changes in the epidemiological situation, availability of medical resources, migration processes, and crisis conditions, particularly martial law.

4. **Interpretability and transparency** – ensuring that forecasts, scenarios, and recommendations are understandable to physicians, epidemiologists, policymakers, and other stakeholders, which is essential for building trust in decisions made using AI.

5. **Humans in the Decision-Making Loop** – using artificial intelligence as a support tool, not a replacement for expert judgment. Final risk assessments and the selection of interventions must involve public health specialists, clinicians, and policymakers.

6. **Ethics and inclusivity** – ensuring the protection of personal health data, preventing algorithmic bias, and addressing the needs of vulnerable populations, including displaced persons, patients with multidrug-resistant tuberculosis, and populations in regions with limited access to healthcare services. The integration of electronic health records, digital platforms, and geospatial data, as well as collaboration among government agencies, international organizations, NGOs, and local communities, and the monitoring of KPIs, are considered in this work not as separate principles but as organizational

and technological mechanisms for implementing the aforementioned methodological principles.

### 5.2. The Mathematical Basis of the SEIRS Model

The mathematical basis is the classical SEIRS (Susceptible–Exposed–Infectious–Recovered–Susceptible) model, which is an extension of the basic SIR model and accounts for the latent period and loss of immunity.

The transition diagram between states is as follows:

$$S \to E \to I \to R \to S. \tag{4}$$

The system of differential equations for the SEIRS model is described as follows:

$$\begin{aligned} \frac{dS}{dt} &= \delta R - \frac{\beta I}{N} S, \\ \frac{dE}{dt} &= \frac{\beta I}{N} S - \sigma E, \\ \frac{dI}{dt} &= \sigma E - \gamma I, \\ \frac{dR}{dt} &= \gamma I - \delta R. \end{aligned} \tag{5}$$

Key model parameters: $\beta$ – infection rate; $\sigma$ – rate of transition from the latent state to the infectious state; $\gamma$ – recovery rate; $\delta$ – rate of immunity loss; $R_0 = \beta/\gamma$ – basic reproduction number.

*Typical dynamics and possibilities for modeling interventions*

The presence of the immunity loss parameter $(\delta > 0)$ leads to cyclical waves of morbidity and the potential establishment of an endemic state. The SEIRS model allows for the assessment of the impact of various management interventions, including quarantine measures (reduction of $\beta$ ), vaccination, and social distancing.

### 5.3. Formalization of the hybrid SEIRS-AI model

Summarizing the results of previous studies presented in publications by the author and co-authors, it is advisable to extend the classical SEIRS compartmental model into **a hybrid multiscale intelligent model** that combines differential equations, geospatial representation, multi-agent systems, and machine learning methods.

Let the epidemiological state of the population at time $t$ be described by the vector:

$$\mathbf{X}(t) = \{S(t), E(t), I(t), R(t)\} , \tag{6}$$

where the components correspond to the classical SEIRS compartments.

Unlike the traditional formulation, **the model parameters are treated as dynamic functions** determined by artificial intelligence methods:

$$\mathbf{\Theta}(t,\mathbf{r}) = \{\beta(t,\mathbf{r}), \sigma(t), \gamma(t,\mathbf{r}), \delta(t)\} , \tag{7}$$

where $\mathbf{r}$ are geospatial coordinates.

Then the system of equations takes the form:

$$\begin{aligned} \frac{dS}{dt} &= \delta(t) R - \beta(t,\mathbf{r}) \frac{I}{N} S, \\ \frac{dE}{dt} &= \beta(t,\mathbf{r}) \frac{I}{N} S - \sigma(t) E, \\ \frac{dI}{dt} &= \sigma(t) E - \gamma(t,\mathbf{r}) I, \\ \frac{dR}{dt} &= \gamma(t,\mathbf{r}) I - \delta(t) R. \end{aligned} \tag{8}$$

***Intelligent model parameterization***

*Estimation of parameters based on machine learning*

The infection and recovery parameters are determined not by constants, but by the results of ML models:

$$\beta(t,\mathbf{r}) = f_\beta(\mathbf{Z}(t,\mathbf{r})) , \tag{9}$$

where $\mathbf{Z}$ is a vector of socioeconomic, demographic, medical, and mobility features, and $f_\beta$ is an ensemble of models (Random Forest, XGBoost, neural networks) tested in studies analyzing tuberculosis and COVID-19 [17–20, 22, 23].

Similarly, the recovery parameter – or the efficiency with which infected individuals transition to the $R$ compartment – is not defined as a constant value, but rather as the output of a machine learning model:

$$\gamma(t,x) = F_\gamma^{ML}(X(t,x), H(t,x)), \tag{10}$$

where $\gamma(t,x)$ is the dynamic recovery parameter at time $t$ for spatial unit $x$; $F_\gamma^{ML}$ is a machine learning function that estimates the parameter $\gamma$; $X(t,x)$ is a vector of socioeconomic, demographic, medical, and mobility features; $H(t,x)$ – a vector of healthcare system characteristics, including access to medical services, staffing, diagnostic capacity, hospital workload, and access to treatment. This notation allows for formally accounting for the degradation or recovery of the healthcare system under conditions of war or other prolonged crises.

### 5.4. Geospatial, multi-agent, and RL extensions of the model

The population is divided into a set of agents:

$$A = \{a_1, a_2, \dots, a_n\} , \tag{11}$$

where each agent is described by a state:

$$a_i(t) = \langle x_i(t), y_i(t), c_i(t), h_i(t) \rangle \tag{12}$$

(geolocation, epidemiological status, behavioral characteristics, access to medical care).

Agent interactions occur in **a geospatial environment such as GeoCity**, which allows for the modeling of:

– local clusters of infection;

– the migration effect;

– various mobility restriction scenarios;

– as demonstrated in studies using GeoSEIR(D) and multi-agent modeling [21].

*Integration of reinforcement learning*

Control interventions are formalized as a reinforcement learning problem:

$$F = \langle \mathcal{S}, \mathcal{A}, P, R \rangle \ , \tag{13}$$

where $\mathcal{S}$ – current epidemiological situation; $\mathcal{A}$ – actions (screening, mobile clinics, quarantine); $R$ – reward function:

$$R = -\alpha I(t) - \beta C(t) \tag{14}$$

(minimizing morbidity and intervention costs).

The optimal strategy $\pi^*$ is determined via Q-learning or deep RL, which generalizes the approach presented in previous and submitted works

*Generalized model structure*

Finally, the methodology is described as a tuple:

$$\mathcal{M}_{AI\text{-}SEIRS} = \langle SEIRS, GeoCity, MAS, ML, RL \rangle \ , \tag{15}$$

where $SEIRS$ – basic epidemiological dynamics; $GeoCity$ – spatial environment; $MAS$ – multi-agent interaction; $ML$ – estimation of parameters and factors; $RL$ – optimization of management decisions.

### 5.5. A comparison of reactive and proactive approaches

In regions with high epidemiological risk, the methodology calls for the implementation of pilot projects using mobile intelligent diagnostic units. The main challenges remain the limited availability of data from temporarily occupied territories and the need to use proxy sources, particularly satellite data. The expected outcome is a 20–30% reduction in morbidity through early detection and optimization of interventions (Table 3).

The comparative assessment of traditional and proactive approaches presented in Table 3 is of a general nature and is based on a combination of several data sets: results of an analysis of current literature on SEIRS/SEIR modeling, the application of artificial intelligence, geospatial, and multi-agent modeling in epidemiology [7–16, 21–28]; the results of the authors' previous studies on modeling the spread of tuberculosis and COVID-19 in a geospatial environment [17–23]; as well as a conceptual comparison of reactive and proactive management scenarios based on criteria such as management focus, tools, adaptability, effectiveness, and cost. Thus, Table 3 reflects not the results of a single clinical or field experiment, but a systematic comparison of expected management effects derived from literature analysis, preliminary modeling, and the logic of the proposed SEIRS-AI hybrid model.

The quantitative ranges of expected reductions in morbidity and costs are scenario-based and require further empirical validation during the pilot implementation of the methodology in regions with elevated epidemiological risk.

**Table 3.** *Comparison of traditional (reactive) and proactive approaches to epidemic management*

| Aspect | Traditional (reactive) approach | A proactive approach based on SEIRS with AI |
|---|---|---|
| **Focus** | Response to detected cases | Prediction and prevention |
| **Tools** | Manual monitoring, paper records | AI-based analytics, digital platforms |
| **Effectiveness** | Delays in diagnosis and response | Reduction in R_0 through forecasting |
| **Adaptability** | Low, especially in crisis situations | High, with real-time updates |
| **Cost** | High due to late interventions | Reduced by 19–37% thanks to proactive measures |

## 6. Discussion

### 6.1. Interpretation of the proposed methodology in the context of contemporary approaches

The proposed project-oriented methodology for proactive epidemic management expands upon traditional epidemiological approaches by integrating mathematical modeling, artificial intelligence, and project management principles. Unlike classic reactive strategies, which focus primarily on recording and processing already identified cases of disease, the proposed approach focuses on risk prediction and the formulation of management decisions before critical scenarios occur.

Integrating the SEIRS model into the project cycle allows the epidemiological process to be viewed not merely as biological dynamics, but as a managed process with clearly defined phases of planning, prevention,

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response, monitoring, and adaptation. This interpretation creates a common language among public health specialists, data analysts, and managers.

*Advantages of the SEIRS-AI-Project Management Hybrid Approach*

One of the key advantages of the proposed methodology is the shift from static parameters of epidemiological models to dynamically controlled parameters estimated using machine learning methods. This allows for the consideration of the influence of socioeconomic, demographic, spatial, and behavioral factors, which are traditionally difficult to formalize in classical models.

Combining SEIRS with geospatial and multi-agent approaches increases the model's sensitivity to local characteristics of infection spread, particularly migration patterns and uneven access to medical resources. The additional integration of reinforcement learning creates a basis for optimizing management interventions, taking into account the trade-off between epidemiological effectiveness and resource constraints.

### 6.2. Practical implications for public health systems

The study results indicate that the proposed methodology has significant potential for practical implementation in public health systems, particularly during prolonged crises. For Ukraine, this means the possibility of:

– early identification of high-risk regions;

– more rational allocation of limited resources (medical personnel, diagnostic tools, hospital beds);

– reducing delays in diagnosis and response;

– increasing the resilience of the healthcare system to external shocks.

The project-oriented nature of the methodology facilitates its integration into existing management structures, as it allows for the formalization of processes, roles, and responsibilities without the need for a complete overhaul of the organizational architecture.

A comparative analysis of traditional reactive and proactive approaches (table in Section 4) demonstrates a fundamental difference in management focus. Reactive approaches are typically characterized by long time delays, low adaptability, and rising costs during crises. In contrast, a proactive approach based on SEIRS and AI allows for a reduction in the basic reproduction number through early forecasting and preventive interventions, potentially reducing total costs by 19–37%.

These results are consistent with recent studies indicating the effectiveness of forecast-oriented strategies compared to late response, particularly for infections with long latent phases, such as tuberculosis.

### 6.3. Study limitations

Despite its advantages, the proposed methodology has a number of limitations. First, the quality of predictions depends heavily on the availability and completeness of data, which is problematic in conditions of military operations and the temporary occupation of certain territories. Second, the use of complex machine learning models increases demands on computational resources and staff qualifications.

In addition, there are ethical and legal challenges related to the processing of personal medical data and potential algorithmic biases, which require additional control and validation mechanisms.

*Areas for further research*

Further research could focus on expanding the methodology by integrating new data sources (e.g., satellite or social media signals), deepening the explainability mechanisms of models, and conducting large-scale pilot implementations in various regions. Particular attention should be paid to validating models in a cross-national context and adapting the methodology to other infectious diseases.

## 7. Conclusions and Recommendations

This article develops and justifies a project-oriented methodology for proactive epidemic management that combines classical SEIRS epidemiological modeling with methods of artificial intelligence, machine learning, geospatial analysis, and reinforcement learning. The proposed approach allows for a shift from reactive responses to infectious disease outbreaks to anticipatory risk management based on predictive analytical models.

It is shown that integrating the SEIRS model into the management project cycle formalizes the epidemiological process as a controlled system with clearly defined phases of planning, prevention, response, monitoring, and adaptation.

The use of dynamic model parameterization based on artificial intelligence allows for the consideration of the influence of socioeconomic, demographic, and spatial factors, as well as the degradation or recovery of the healthcare system under crisis conditions.

Extending the classical SEIRS model to a hybrid multilevel intelligent structure, which includes geospatial representation, multi-agent systems, and optimization of management interventions, forms a universal methodological framework for forecasting and preventing infectious diseases. The comparative analysis conducted indicates that a proactive approach based on SEIRS and AI has greater adaptability, potentially reduces the basic reproduction number, and allows for cost reduction through early and targeted interventions.

The methodology has particular practical value for Ukraine, where prolonged crisis factors, military operations, and limited data availability significantly complicate traditional epidemiological surveillance. The proposed approach creates a foundation for enhancing the resilience of the public health system and more effective use of limited resources.

*Practical Recommendations*

Based on the results obtained, the following recommendations are appropriate:

1. **Implementation of a project-oriented approach** to epidemic management at the level of national and regional public health programs, with a clear definition of phases, roles, and performance indicators.

2. **Integration of digital platforms and AI-based analytics** with existing epidemiological surveillance systems to ensure continuous real-time data collection, analysis, and interpretation.

3. **Use of the SEIRS model with dynamic parameterization** to forecast infections with long latent phases, particularly tuberculosis, taking into account regional characteristics and migration patterns.

4. **Pilot implementation of the methodology** in regions with elevated epidemiological risk, followed by validation of results and scaling up at the national level.

5. **Strengthening cross-sectoral collaboration** between health authorities, think tanks, research institutions, and non-governmental organizations to ensure inclusive and ethical decision-making.

6. **Further research** should focus on the empirical validation of the proposed methodology, expanding datasets, improving the interpretability of AI models, and adapting the methodology to other infectious diseases.

## Conflict of interest

The authors declare that they have no conflicts of interest, including financial, personal, authorial, or any other nature, that could influence the study or the results published in this article.

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## Data availability

Data will be provided upon reasonable request.

## Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies to write this paper.

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# ПРОЄКТНО-ОРІЄНТОВАНА МЕТОДОЛОГІЯ ПРОАКТИВНОГО УПРАВЛІННЯ ЕПІДЕМІЯМИ НА ОСНОВІ ШТУЧНОГО ІНТЕЛЕКТУ Й МОДЕЛЕЙ SEIRS

**Предметом дослідження** в статті є процеси проактивного управління епідеміями як складними соціально-медичними системами в умовах високої невизначеності, обмеженості ресурсів і динамічних зовнішніх впливів, зокрема із застосуванням математичного епідеміологічного моделювання та інтелектуальних цифрових технологій. **Мета роботи** полягає в створенні проєктно-орієнтованої методології управління епідеміями на основі інтеграції класичної моделі SEIRS зі штучним інтелектом, машинним навчанням і цифровими системами підтримки прийняття управлінських рішень, що забезпечує перехід від реактивного реагування до проактивного прогнозування й запобігання спалахам інфекційних захворювань. У статті необхідно виконати такі **завдання:** сформувати концептуальну й процесну модель проактивного управління епідеміями в межах проєктного підходу; розробити інтегровану архітектуру збору, аналізу та інтерпретації епідеміологічних показників; адаптувати компартментну модель SEIRS до умов динамічної параметризації з використанням методів машинного навчання; обґрунтувати застосування геопросторових і мультиагентних підходів для врахування неоднорідності поширення інфекцій; визначити роль інтелектуальних методів оптимізації управлінських втручань у проєктному циклі протидії епідеміям. Упроваджено такі **методи:** математичне моделювання епідеміологічних процесів на основі систем диференціальних рівнянь SEIRS; машинне навчання й ансамблеве прогнозування для динамічного оцінювання параметрів моделі; геопросторовий аналіз і мультиагентне моделювання для відтворення мобільності населення й просторових ризиків; навчання з підкріпленням для оптимізації управлінських рішень; проєктно-орієнтовані підходи до організації та адаптації управлінських процесів. Досягнуто таких **результатів:** сформульовано принципи проактивного управління епідеміями на основі інтеграції епідеміологічного моделювання й штучного інтелекту; запропоновано проєктно-орієнтовану методологію, що поєднує цикл управління проєктом із фазами моделі SEIRS; розроблено узагальнену структуру гібридної інтелектуальної моделі, здатної адаптуватися до різних типів інфекційних захворювань, зокрема туберкульозу та COVID-19; обґрунтовано можливість підвищення ефективності раннього виявлення ризиків і раціонального розподілу ресурсів у кризових умовах. **Висновки:** застосування запропонованої проєктно-орієнтованої методології та інтегрованої моделі SEIRS зі штучним інтелектом створює підґрунтя для переходу до проактивного управління епідеміями, підвищує адаптивність систем громадського здоров’я та може бути використане як універсальний методологічний каркас для розроблення інтелектуальних систем прогнозування й запобігання епідеміям у складних і нестабільних середовищах.

**Ключові слова:** проактивне управління епідеміями; проєктно-орієнтована методологія; штучний інтелект; модель SEIRS; машинне навчання; цифрове здоров’я; епідеміологічне прогнозування; системи підтримки прийняття рішень.

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