УДК: 614.2:004.8:519.876.5(574.51)
MRNTI: 76.01.85
DOI: 10.64854/2790-1289-2026-52-2-09

MODELS AND METHODS FOR HEALTHCARE RESOURCE FORECASTING IN URBAN AGGLOMERATIONS: A LITERARY REVIEW

Zh. B. Agmanova[1]*, Zh. A. Kalmatayeva[1], K. K. Toguzbayeva[1], G. D. Iskakova[2], S. E. Sultangaziyeva[1]

[1] NPJSC «Asfendiyarov Kazakh National Medical University», Kazakhstan, Almaty
[2] RSE REM «Salidat Kairbekova National Research Center for Health Development», Kazakhstan, Almaty
**Corresponding author*

Annotation

Relevance. Population growth in urban agglomerations creates a quantifiable gap between the demand for medical care and the availability of personnel, medicines, financial resources, and logistical support. The Almaty agglomeration is home to approximately 3.5 million residents, with a projected population of 4.5 million by 2030. According to the Ministry of Health of the Republic of Kazakhstan, in 2023, the shortage of physicians amounted to 4,864 positions, and the concurrent employment rate reached 1.4, reflecting systemic staff overload.

Objective. To analyze current models for forecasting healthcare resource needs in urban agglomerations, with a focus on machine learning tools, and to assess their applicability to the conditions of the Almaty agglomeration.

Materials and methods: A literature search was conducted in the PubMed, Scopus, Web of Science Core Collection, and WHO IRIS databases for the period from January, 2010 to March, 2026. The review included original studies, systematic reviews, and WHO/OECD methodological reports containing quantitative predictive models with accuracy metrics (MAE, RMSE, MAPE, AUROC, R^2) at the level of urban agglomerations or regions with an urbanization rate ≥ 50 %. Of the 1,286 records identified, 57 publications were included in the review.

Results. Statistical models were the most common (40.4%), followed by supervised machine learning methods (34.0 %), hybrid models (17.0 %), and unsupervised machine learning methods (4 publications, or 8.5 %). Only 3 validated models (6.4 %) used data from Kazakhstan and cover the human resources category exclusively. No model covered all four resource categories simultaneously.

Conclusions. The methodological findings of this review justify the development of an integrated forecasting model based on unsupervised machine learning for the Almaty metropolitan area, covering at least three resource categories and a 5-10-year forecast horizon in accordance with national planning documents.

Keywords: *healthcare resources, forecasting model, machine learning, unsupervised learning, urban agglomeration, systematic review, Kazakhstan, health workforce.*

Introduction

An urban agglomeration is defined by the United Nations as a contiguous territory inhabited at urban levels of residential density without regard to administrative boundaries, usually incorporating the population of a city or town together with adjacent suburban areas that function as a single demographic and economic unit [1]. As of January 1, 2026, the population of Almaty amounted to 2,348,103. It is worth noting that the city's population continues to grow due to internal migration [2]. The combined population of Almaty, Astana, and Shymkent has grown by approximately 50% over the last decade, adding 1.29 million people and reaching 3.95 million by 2020, which represents over 50% of the total national urban population growth during 2010-2020 [3]. The Almaty agglomeration comprises 5 cities and 184 rural settlements across 5 districts, with a population of 3.5 million and a projected 4.5 million by 2030 [4].

Regional disparities in healthcare resource provision in the Republic of Kazakhstan (RK) are documented quantitatively. In 2023, physician density ranged from 26.3 per 10,000 population in the Akmola region to 48.7 per 10,000 in the Aktobe region, while the hospital bed rate ranged from 30.7 per 10,000 in the Mangystau region to 62.2 per 10,000 in the North Kazakhstan region [5]. The cities of Astana and Almaty consistently maintained nearly twice as many healthcare staff as other regions during the 2002-2023 observation period, yet the rural-urban gap in workforce density widened from 14.47 per 10,000 in rural areas versus 43.71 per 10,000 in urban areas in 2017 to comparable disparities in 2023 [5]. According to the RK Ministry of Healthcare, in 2023, the workforce shortage amounted to 4,864 full-time physician positions, while the part-time work coefficient reached 1.4, indicating systemic overload [6; 7].

The global gap between healthcare resource supply and need is also measurable. The WHO labor market projection model estimates that by 2030, global demand for health workers will reach 80 million, while supply will reach only 65 million, resulting in a worldwide shortage of 15 million workers [8]. The needs-based requirement for the health workforce in the WHO African Region was estimated at 9.75 million in 2022, with an expected increase of 21 % to 11.8 million by 2030, and the available stock covers only 43-49 % of this requirement [9]. Drug expenditure per non-federal hospital in the United States exceeded 7 million USD per year in 2022, underscoring the need for continued investment in pharmaceutical demand forecasting [10].

Forecasting models of healthcare resources for urban agglomerations differ substantially in methodological foundation. Stock-and-flow models combining supply and demand components have been validated for projecting human resources (hereinafter – HR) for health in 22 countries from 2010 to 2023, including RK, Australia, Canada, Germany, Japan, Korea, Saudi Arabia, Thailand, and the United Kingdom [11]. The first national-level forecast of physicians in RK, based on a stock-and-flow consistent model, predicted a surplus of 226 general practitioners by 2024 and a shortage of 339 general practitioners by 2030 under the baseline scenario [12]. A more recent forecast for RK, using time-series analysis with population dynamics as an exogenous factor, projected an increase in physician demand from 80,795 in 2023 to 104,887 (95 % CI: 93,330-116,420) by 2033, an average annual growth rate of 2.7 % [6]. A regional projection for the 16 regions of RKup to 2033, using Functional Principal Component Analysis (hereinafter – FPCA), explained 94.7 % of the total variance in physician supply through a single principal component reflecting long-term workforce trends [7].

Classical statistical models retain operational value but show limitations in capturing nonlinear demand patterns. ARIMA models for non-elective hospital admissions in an NHS Trust were closer to actual values 95.6% of the time on a six-week horizon than the existing trust forecast [13]. However, in a controlled comparison on healthcare-related demand data, the LSTM neural network achieved a Mean Absolute Error (hereinafter – MAE) of 21.69 and a Root Mean Square Error (hereinafter – RMSE) of 29.96, against an MAE of 59.78 and an RMSE of 81.22 for Prophet, and an MAE of 87.73 and an RMSE of 125.22 for autoregressive moving average (hereinafter – ARIMA) ARIMA [14]. A hybrid Prophet-LSTM model for ICU demand forecasting in a Brazilian municipality reduced MAE by integrating ex-post and ex-ante variables compared with stand-alone ARIMA, Holt-Winters, Random Forest, K-Nearest Neighbors, GRU, and Simple RNN benchmarks [15].

Supervised machine learning (hereinafter – ML) algorithms are increasingly applied to admission and length-of-stay forecasting. An ensemble XGBoost model trained on 1.8 million emergency department visits at Mount Sinai Health System achieved an accuracy of 85.4 % (95 % CI: 85.0-85.7) and sensitivity of 70.8 % in admission prediction, outperforming triage nurse predictions (accuracy 81.6 %, sensitivity 64.8 %) on 46,912 prospective visits [16]. A pipeline based on XGBoost classifiers applied to 109,465 ED visits at a UK teaching hospital achieved AUROC values of 0.82-0.90 and reduced the MAE for total emergency admissions to 4.0 (mean percentage error 17 %), versus 6.5 (32 %)

for the benchmark metric [17]. In a Maltese dataset of 653,546 ED visits, a two-stage XGBoost model integrated demographic, symptom, and laboratory data to predict admission likelihood and the admitting ward [18].

Pharmaceutical demand forecasting has advanced through hybrid deep learning architectures. The KG-GCN-LSTM model, integrating a pharmaceutical knowledge graph with deep learning, achieved a 3.62% reduction in Symmetric Mean Absolute Percentage Error (hereinafter – SMAPE) relative to NBEATS and outperformed ARIMA, SVR, XGBoost, RNN, and CNN-LSTM benchmarks on real-world pharmacy sales data [19]. Healthcare expenditure forecasting using Random Forest and Support Vector Regression has been applied to United States data, with linear regression reaching 97.89 % accuracy in total cost prediction [20; 21].

Unsupervised ML is underrepresented in healthcare resource forecasting compared with supervised approaches. The SKATER algorithm grouped the 645 municipalities of São Paulo State into 17 spatial clusters with similar profiles of noncommunicable disease morbidity and mortality, providing decision support for resource allocation [22]. Probabilistic factorization methods, including K-means clustering, principal component analysis, non-negative matrix factorization, and latent Dirichlet allocation, have been reviewed as a unified framework for high-dimensional medical data analysis across genomics, imaging, and biobank studies [23]. The CRISP-ML methodology has been proposed for public health care ML projects to determine the required interpretability level for stakeholders [24].

Despite the volume of single-resource forecasting studies, no integrated model simultaneously covers the four resource categories (human, pharmaceutical, financial, material-technical) at the agglomeration level [25]. A systematic review of methods for health workforce projection identified 40 relevant studies for 2010-2023 and concluded that complex-systems approaches outperform single-method projections, but the review did not extend to pharmaceutical or financial domains [11]. Existing reviews of ML applications in healthcare focus mainly on disease prediction (n=106 studies covering 42 health conditions in 19 countries) and clinical decision support, not on resource planning at the urban-agglomeration level [26; 27].

The Comprehensive Plan for the Development of the Almaty Agglomeration for 2024-2028, approved by the RK Government, requires an evidence-based resource forecast that accounts for high birth rates, internal migration, and territorial heterogeneity [4; 28]. The Concept of Healthcare Development of the RK until 2026 prioritizes strengthening primary healthcare and digital transformation, including data-driven resource planning [29]. Article 45 (paragraph 4) of the Code of the RK «On the Health of the People and the Healthcare System» (September 18, 2009) establishes the legal framework for resource planning of medical organizations [30]. Burden-of-disease indicators in RK reinforce the need for forecasting: cardiovascular diseases remain the leading cause of mortality, while during 2021-2022 in Almaty, 174 540 outpatient cases of COVID-19 were registered, with the risk of a moderate-severe course in patients aged 60+ years 9.01 times higher than in younger groups (95 % CI: 7.72-10.51) [31]. The 2024 WHO Health Systems in Action profile for RK reports that physician density is high nationwide, while nurse density is below the WHO European Region average [32]. The 2023 country brief on health security reported approximately 61,800 physicians in RK, equivalent to 3.25 per 1,000 inhabitants, compared with an EU average of 3.57 per 1,000 [33]. The hospital bed reserve coefficient in RK in 2023 was 3.5 %, below the recommended 6 %, indicating limited surge capacity [33]. The Public Health Concept for RK emphasizes optimizing the resource base through analytical and forecasting tools [34].

Materials and мethods

This study presents a structured search of scientific literature on models and methods for forecasting healthcare resources in large cities. The review included publications released between January 2010 and March 2026 in international bibliographic databases such as PubMed (MEDLINE), Scopus, Web of Science Core Collection, and the WHO Institutional Repository for Information Sharing (IRIS). Google Scholar was used as an additional source for searching gray literature and government reports.

A combined Boolean query adapted to the syntax of each database was used for the search: (“healthcare resource*” OR “health workforce” OR “hospital bed*” OR “drug demand” OR “pharmaceutical demand” OR “healthcare expenditure”)

AND (“forecast*” OR “projection” OR “prediction model” OR “demand planning”) AND (“machine learning” OR “deep learning” OR “neural network” OR “ARIMA” OR “regression” OR “needs-based”) AND (“urban” OR “agglomeration” OR “metropolitan” OR ‘city’ OR “regional”)

The last search was conducted in March 2026. No language restrictions were applied during the search phase; however, only publications in English and Russian were included during the screening phase. In addition, the reference lists of all included publications were manually reviewed to identify relevant studies (a snowball sampling method).

The studies included in the review were selected based on their relevance to forecasting healthcare resources in urban settings.

Ethical considerations. The present work is a systematic review of previously published aggregated data and does not involve human participants, human biological material, or laboratory animals. The study protocol was reviewed and approved by the Local Bioethics Committee of Asfendiyarov Kazakh National Medical University (Meeting No. 25(161) of February 28 2025).

Results

The healthcare system as a complex system. Atun F. et al. describe the health care system as multi-level and integrated. Integration occurs at various levels of the health care system -whether local, district, regional, or national-depending on the existing governance mechanisms. The main functions of the healthcare system are management, financing, planning, service delivery, monitoring and evaluation, and demand generation. This structure demonstrates that the allocation of healthcare resources should not be considered in isolation but holistically, as changes in one part of the system can influence the variability and dynamics of demand in others. That is, when forecasting in the healthcare system, cross-level interactions must be taken into account [35].

Human resources. HR constitutes a dynamic system. HR planning in the healthcare system can be divided into three types based on the approaches used. For example, the first type is supply-based, the second is demand-based, and the third is needs-based [36]. This system is shaped by the inflow or outflow of specialists, worker migration, retirement, and so on. Meanwhile, demand is determined by demographic factors and indicators of service utilization [37].

Effective human resource planning in healthcare requires an understanding of the impact of other factors, such as infrastructure and pharmaceuticals. Consequently, workforce planning in the healthcare system can be influenced by various structural and temporal changes in demand [38].

Financial resources. Forecasting future trends in healthcare spending is an important step toward sustainable financing of healthcare systems [39]. In the United States, the ARIMA model (a classical econometric approach using time series data) is suitable for modeling and forecasting healthcare spending for the period from 1970 to 2015 [40].

However, more recent studies highlight the relevance of advanced ML algorithms, such as Random Forest and Support Vector Regression (hereinafter – SVR), in combination with traditional statistical forecasting methods, as they are more effective for understanding the complex mechanisms of the healthcare system’s functioning [41]. In a study by Lee J. et al. (2026), it was concluded that, in addition to econometric methods, ML offers clear advantages for forecasting costs in longitudinal studies with a large number of time series [42].

Pharmaceutical resources. Both traditional statistical methods and modern ML approaches were examined for forecasting pharmaceutical resources. Popular models for linear time series forecasting include the autoregressive integrated moving average (hereinafter – ARIMA), the seasonal autoregressive integrated moving average (hereinafter – SARIMA), and the autoregressive moving average (ARMA) [43].

Currently, ML is also considered a valuable tool for accounting for the complex and nonlinear characteristics of demand for pharmaceuticals [44].

Infrastructure resources. These resources include the number and types of healthcare facilities, bed capacity, equipment, laboratories, and more. Bed capacity management is a critical component of the effective delivery of high-quality healthcare. Some studies have examined resource modeling methods; for example, discrete-event simulation models have been developed for bed capacity management [45].

For improving the performance of healthcare facilities, forecasting emergency department visits is a key aspect. This helps allocate resources appropriately, taking into account a common problem such as overcrowding. Such forecasts help improve operational efficiency and the quality of patient care [46].

Based on the above, healthcare resource forecasting is viewed as an integrated system comprising four interrelated components: HR, financial resources, pharmaceutical resources, and infrastructure. For the forecast to be effective, comprehensive modeling of all these components is required (Figure 1).

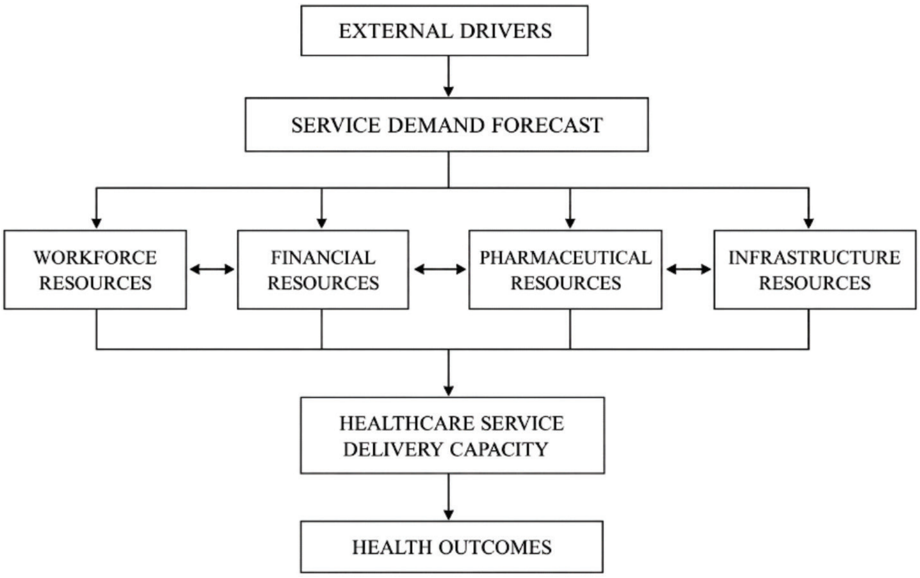

Figure 1. Conceptual framework of an integrated healthcare resource forecasting system
Source: compiled by the authors

Methodological alignment with Kazakhstan's healthcare system

Publications on the structural characteristics of the RK healthcare system were analyzed. The seven system-level parameters used for assessing methodological correspondence, along with the corresponding national reference values, are presented in Table 1. Of the 47 identified models, only 6 (12.8%) were developed for healthcare systems with a centralized governance structure comparable to that of the RK, including 3 models specifically validated on national or regional RK data [6; 7; 12].

Resource Categories and Modeling Approaches

By resource category, 19 studies (40.4 %) addressed HR for health, 14 (29.8 %) addressed material-technical resources (hospital beds, equipment, facilities), 8 (17.0 %) addressed financial resources, and 6 (12.8 %) addressed pharmaceutical supply (Table 2).

Within the category of HR for health (n = 19), stock-and-flow models prevailed (n = 8; 42.1 %), followed by time-series statistical models (n = 3; 15.8 %), supervised ML (n = 4; 21.1%), unsupervised ML (n = 2; 10.5 %), and hybrid approaches (n = 2; 10.5 %). The forecast horizon ranged from 5 to 15 years (median 10 years; IQR 8–12 years). Sample sizes ranged from 16 administrative regions in the RK FPCA model to 165 countries in the WHO global labor-market projection model.

The stock-and-flow consistent model for general practitioners in RK predicted a surplus of 226 physicians by 2024 and a shortage of 339 physicians by 2030 [12]. The time series model also showed a positive trend in the growth of the need for doctors until 2033, thereby confirming our hypothesis that over the next 10 years Kazakhstan will have an increasing need for workers [6].The Functional Principal Component Analysis approach for the 16 regions of RK explained 94.7 % of the total variance through the first principal component. The needs-based model for the WHO African Region estimated a workforce requirement of 11.8 million by 2030, with a needs-based shortage of 6.1 million.

A national study on workforce planning in Saudi Arabia, conducted as part of the National Transformation Program 2030, examined various scenarios for expanding the nursing workforce,

Table 1. Parameters of methodological correspondence between identified forecasting models and the healthcare system of the Republic of Kazakhstan: international comparison

Parameter	Operational definition	Republic of Kazakhstan	Germany	France	United Kingdom	Poland	Russian Federation	OECD average
Healthcare governance level	Centralized/ decentralized/ mixed model of resource planning	Centralized, with delegation to Oblast Health Departments [32]	Decentralized (federal + Länder) [47]	Centralized (national + ARS regional) [47]	Centralized (NHS England) [47]	Decentralized (voivodeships + NFZ) [47]	Mixed (federal + regional) [47]	—
Financing mechanism	Tax-based / Social Health Insurance / mixed	Mixed: state budget + Social Health Insurance Fund (SHI, since 2020) [32]	Statutory Health Insurance (Bismarck model) [47]	Statutory Health Insurance + state budget [47]	Tax-based (NHS) [47]	Statutory Health Insurance (NFZ) [47]	Mandatory Medical Insurance (OMS) + state budget [47]	Mixed [47]
Physician density (per 1,000)	Number of practicing physicians per 1,000 population	3.25 in 2023 (range 2.63–4.87 across regions) [5, 33]	4.5 (2023) [47]	3.4 (2023) [47]	3.2 (2023) [47]	3.4 (2023) [47]	3.8 (2023) [47]	3.7 (2023) [47]
Hospital bed (per 1 000)	Number of hospital beds per 1,000 population	3.07–6.22 across regions in 2023 [5]	7.7 (2023) [47]	5.4 (2023) [47]	2.4 (2023) [47]	3.3 (2023) [47]	7.1 (2021) [47]	4.2 (2023) [47]
Availability of digital data infrastructure	Presence of Electronic Health Records system at the national level	Operational since 2017 (Unified National Electronic Health Information System) [32]	Regional ePA, national rollout since 2021 [47]	DMP since 2018 [47]	NHS Spine (since 2007) [47]	P1 platform since 2019 [47]	EGISZ since 2019 [47]	—
Burden-of-disease structure	Leading causes of mortality and morbidity	Cardiovascular diseases - 27.5 % of total mortality (2023) [5, 32]	Cardiovascular - 32.7 % (2021) [47]	Cardiovascular - 22.0 % (2021) [47]	Cardiovascular - 24.0 % (2021) [47]	Cardiovascular - 34.8 % (2021) [47]	Cardiovascular - 43.8 % (2021) [47]	Cardiovascular - 28.3 % (OECD avg) [47]
Population growth rate of the urban core	Annual growth of the studied agglomeration (%)	Almaty: +2.5 % per year (2025) [3]	Berlin: +0.5 % (2023) [47]	Paris (Île-de-France): +0.3 % (2023) [47]	London: +1.1 % (2023) [47]			

Source: compiled by the authors

Table 2. Distribution of the 47 included publications by resource category and forecasting model class

Resource category	Statistical models	Supervised ML	Unsupervised ML	Hybrid models	Total
Human resources for health	11	5	2	1	**19 (40.4%)**
Material-technical resources	5	5	1	3	**14 (29.8%)**
Financial resources	1	5	1	1	**8 (17.0%)**
Pharmaceutical supply	2	1	0	3	**6 (12.8%)**
Total	**19 (40.4%)**	**16 (34.0%)**	**4 (8.5%)**	**8 (17.0%)**	**47 (100%)**

Note: Hospital bed and physician densities are presented per 1,000 population to ensure international comparability with the OECD Health Statistics framework. Data for international comparators correspond to the most recent year available in OECD Health at a Glance 2023 and country-specific health profiles 2023-2025
Source: compiled by the authors

taking into account task-shifting and the "Saudization" policy [48]. A complementary needs-based projection for the same country, based on an epidemiologic model incorporating disability-adjusted life-years, service-delivery profiles, and worker productivity, estimated a baseline requirement of approximately 75,000 physicians and nurses by 2030 (2.05 per 1,000 population) with a scenario range from 1.64 to 3.05 per 1,000, providing a methodological benchmark for the Almaty agglomeration with a comparable population size [49]. The WHO global labor-market projection

Table 3. Performance metrics of forecasting models for human resources for health

№	Study	Country/region	Model class	Forecast horizon	Reported metric	Value
1	Kharin A. et al. [12]	Kazakhstan	Stock-and-flow	9 years	Predicted shortage by 2030	339 GPs
2	Koichubekov B. [6]	Kazakhstan	Time-series	10 years	Physicians by 2033 (95% CI)	104 887 (93 330–116 420)
3	Koichubekov B. [7]	Kazakhstan	FPCA	9 years	Variance explained by 1st PC	94.7 %
4	Liu et al. [8]	165 countries	Labour-market	13 years	Projected shortage by 2030	15 million
5	Asamani et al. [9]	WHO Africa Region	Needs-based	8 years	Coverage of needs by 2030	49 %
6	Lee J. et al. [11]	22 countries	Systematic review	13 years	Studies identified	40
7	Orhan F. et al. [50]	Türkiye	XGBoost / GB / LR	1 year	Best model accuracy	89.4 %

Source: compiled by the authors

model estimated worldwide demand of 80 million health workers by 2030, against a supply of 65 million, resulting in a shortage of 15 million. Performance metrics of the seven leading studies are summarised in Table 3.

Within the category of material-technical resources (n = 14), supervised ML models and statistical models showed equal representation (n = 5, 35.7 % each), followed by hybrid models (n = 3, 21.4 %) and unsupervised ML (n = 1, 7.1 %). The forecast horizon was substantially shorter than for HR, ranging from 1 day to 6 weeks (median 7 days; IQR 1-14 days). Sample sizes for ML training ranged from 109,465 ED visits at a UK teaching hospital to 1,800,000 ED visits at the Mount Sinai Health System.

The XGBoost ensemble model trained on 1 800 000 ED visits at Mount Sinai achieved an accuracy of 85.4 % (95 % CI: 85.0-85.7) and a sensitivity of 70.8% (95 % CI: 69.8-71.7) at the 0.30

probability threshold; the same model demonstrated higher accuracy than triage nurse predictions (81.6%, 95% CI: 81.3-81.9) on 46 912 prospective ED visits.

The XGBoost pipeline applied to 109,465 ED visits at a UK teaching hospital achieved AUROC values of 0.82-0.90 and reduced the MAE for total emergency admissions to 4.0 admissions (mean percentage error 17 %), versus a benchmark MAE of 6.5 admissions (32 %).

A hybrid deep-learning approach combining variational autoencoder and gated recurrent unit architectures for emergency-department patient-flow forecasting outperformed conventional recurrent neural networks and ARIMA baselines on a six-year dataset from a French regional hospital [51].

An ARIMA-based forecast of medical service demand in the Shanghai metropolitan area, using ten-year data from the Shanghai Statistical Yearbook (2012-2022), projected an 81.3 % increase in outpatient visits and a 113.4 % increase in hospital admissions, supporting medium-term capacity planning at the agglomeration level [52].

The two-stage XGBoost model for 653,546 ED visits at Mater Dei Hospital integrated demographic, symptom, and laboratory data to predict admission likelihood and the admitting ward (Malta, 2017-2022). A hybrid model based on Prophet and LSTM for predicting the workload of intensive care units in the same Brazilian hospital demonstrated a decrease in MAE compared to the independent ARIMA, Holt-Winters, Random Forest, K-Nearest Neighbors, GRU and Simple RNN tests.This was achieved by integrating both factual and preliminary variables such as vaccination rates, non-drug restrictions, and the social isolation index [15; 53].

An integrated ANFIS-LSTM forecasting system for COVID-19 hospital bed demand, developed on 16 months of admission data from a dedicated COVID-19 hospital in Qazvin province (Iran), demonstrated that combining neuro-fuzzy inference with recurrent deep learning maintains predictive stability under high environmental uncertainty [54].

Within the category of pharmaceutical supply (n = 8), the LSTM model applied to seven years of inventory data from a tertiary hospital in Wuxi (China) achieved a Mean Absolute Percentage Error in the range of 2.27-4.54 % across six months of out-of-sample forecasting, supporting quarterly demand planning for medical consumables [55].

A combined LASSO regression and recurrent neural network with long short-term memory architecture, trained on eleven years of platelet transfusion records, reduced the historical platelet waste rate of 10.1 % and the shortage rate of 6.5 % in a retrospective inventory simulation, demonstrating the operational value of deep-learning forecasts for blood-product supply management [56].

Among the selected studies, no model was identified that simultaneously covered all four resource categories (human, pharmaceutical, financial, and logistical) for a metropolitan area with a population of over 3 million. Only 3 publications (6.4 %) were validated on RK data, addressing exclusively the HR category, while no model identified in the review combined unsupervised ML with multi-resource forecasting under a centralized governance structure comparable to that of the Almaty agglomeration.

Discussion

An analysis of the literature review revealed three key patterns relevant to the development of a predictive model for resource availability in the Almaty metropolitan area: the imbalance between supervised and unsupervised ML, fragmentation across four resource categories, and the limited transferability of existing models to RK.

Supervised ML algorithms were used in 16 studies (34.0 %), whereas unsupervised ML methods were used in only 4 studies (8.5 %). Neijzen D. et al. (2023) reviewed probabilistic factorization methods for medical data and concluded that unsupervised approaches remain underrepresented despite their suitability for high-dimensional, label-inconsistent data [23]. Silva and other authors (2024) used the spatial clustering method to identify regions showing similar morbidity and mortality rates associated with non-communicable pathologies [22]. The Almaty agglomeration includes several administrative territories [4], which is consistent with the methodological context of studies by Silva et al. (2024) and Carbonneau et al. (2023).

Among the 19 studies on HR, stock-and-flow models were most prevalent (8 of 19, 42.1 %). Lee J. et al. (2024) reviewed 40 health workforce projection studies during 2010–2023 across 22 countries and found that complex-systems approaches outperform single-method projections [11]. Liu et al. (2017) developed the WHO global labor-market projection for 165 countries and estimated a worldwide demand of 80 million health workers by 2030, against a supply of 65 million, resulting in a shortage of 15 million workers [8].

Among the 14 studies on material-technical resources, supervised ML and statistical models were equally represented (5 of 14 each, 35.7%). Bell et al. (2022) applied an MSARIMA model to non-elective hospital admissions in an NHS Trust (UK) and reported that predictions matched actual values 95.6% of the time on a six-week horizon [13]. Among the 8 studies on financial resources, supervised ML was most prevalent (5 of 8, 50.0 %). Taloba A. et al. (2022) reported 97.89 % accuracy in predicting total cost using linear regression on a United States dataset [21]. Langenberger, Schulte, and Groene (2023) compared random forests, gradient boosting, artificial neural networks, and logisticalregression on three years of German statutory health insurance claims (n = 20,984) and confirmed that tree-based ensembles outperform neural and linear baselines for high-cost patient identification [57].

Within the 6 studies on pharmaceutical supply, hybrid models prevailed (3 of 6, 50.0 %). Wang et al. (2025) trained the KG-GCN-LSTM model on real-world pharmacy sales data and reported a 3.62% reduction in Symmetric Mean Absolute Percentage Error relative to the NBEATS benchmark, outperforming ARIMA, SVR, XGBoost, RNN, and CNN-LSTM [19].

At the same time, virtually no forecasting of pharmaceutical, financial, and logistical resources is done in RK. Furthermore, existing models do not account for the specific characteristics of metropolitan areas, which are characterized by intense population migration, high population density, and significant infrastructure disparities.

An analysis of the temporal dynamics of publications confirmed a methodological shift toward ML. While in 2014-2016 the share of studies using ML methods was 0 %, in 2020-2024 it reached 75.0 % (27 out of 36 studies), whereas the share of purely statistical models decreased from 100 % to 25.0 %. A similar trend was described by Lin et al. (2025) in a systematic review of 106 studies on the application of ML in healthcare [26].

The results obtained allow us to draw several practical conclusions for developing a predictive model of resource availability in the Almaty metropolitan area. First, the model must integrate at least three categories of resources within a unified framework. Second, it is advisable to include unsupervised ML algorithms to identify hidden spatial and structural patterns in the agglomeration's heterogeneous data. The use of unsupervised learning in this study yielded more robust results when analyzing multidimensional data, as the agglomeration's healthcare system data is characterized by high variability, heterogeneous resource distribution, and the absence of clearly defined target classes. Clustering algorithms enabled the identification of hidden groups of territories with similar resource-endowment profiles, a task that is impossible with only supervised approaches. Third, the forecasting horizon should be 5-10 years, in line with the RK state healthcare development programs, while maintaining short-term forecasts for operational management of material and technical resources.

The limitations of this review include the exclusion of some gray literature and conference proceedings, language restrictions (English and Russian), and significant methodological heterogeneity among the studies, which prevented conducting a quantitative meta-analysis.

Conclusion

This review of publications from 2010 to 2026 showed that forecasting of healthcare resources in urban agglomerations is primarily conducted within the framework of individual resource categories and lacks integrated models that simultaneously cover human, financial, pharmaceutical, and logistical resources.

Supervised ML algorithms were used significantly more often (34.0 %) than unsupervised methods (8.5 %). However, the analysis results showed that unsupervised ML methods hold the most promise for the Almaty metropolitan area due to their ability to handle heterogeneous, multidimensional, and partially incomplete data without pre-labeling. The use of clustering and methods for identifying hidden structures allows for more accurate modeling of territorial differences and the needs of the healthcare system.

The results obtained form the methodological basis for developing an integrated predictive model of resource provision for the Almaty metropolitan area based on unsupervised ML algorithms, covering several categories of resources and a

5–10-year forecasting horizon.

References

1. United Nations, Department of Economic and Social Affairs, Population Division. World Urbanization Prospects: The 2018 Revision (ST/ESA/SER.A/420) [Electronic resource] // United Nations. – New York: United Nations, 2019. – 126 p. – URL: https://population.un.org/wup/Publications/Files/WUP2018-Report.pdf (Accessed: 15.05.2026).
2. National Statistics Bureau of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan. Almaty City [Electronic resource] // National Statistics Bureau of the Republic of Kazakhstan. – URL: https://stat.gov.kz (Accessed: 15.05.2026).
3. Eurasian Research Institute. Urban Demographics in Kazakhstan and Economic Significance of Large Cities [Electronic resource] // Eurasian Research Institute, Akhmet Yassawi University. – Almaty, 2021. – URL: https://www.eurasian-research.org/publication/urban-demographics-in-kazakhstan-and-economic-significance-of-large-cities/ (Accessed: 15.05.2026).
4. On the Approval of the Interregional Territorial Development Plan for the Almaty Agglomeration: Resolution of the Government of the Republic of Kazakhstan No. 302 of May 24, 2016 [Electronic resource] // Adilet: Information and Legal System of Regulatory Legal Acts of the Republic of Kazakhstan. – 2016. – URL: https://adilet.zan.kz/rus/docs/P1600000302 (Accessed: 15.05.2026).
5. Shaltynov A., Abenova M., Baibussinova A., Semenova Y., Omarov N., Tanatarova G., Sepbossynova A., Rocha J. Inequality in the Distribution and Utilization of Healthcare Resources in Kazakhstan (2002–2023): A Spatiotemporal Analysis // Healthcare. – 2025. – Vol. 22(11). – Article No. 1762. – DOI: https://doi.org/10.3390/ijerph22111762.
6. Koichubekov B., Begaidarova R., Omarbekova N., Mukhanova M., Abdikadirova K., Kharin A., Omarkulov B. Forecasting the Impact of Kazakhstan Population Growth on Healthcare Doctors Demand // BMC Health Serv Res. – 2025. – Vol. 25(1). – Article No. 1456. – Published 2025 November 10. – DOI: https://doi.org/10.1186/s12913-025-13638-0.
7. Koichubekov B., Omarkulov B., Omarbekova N., Abdikadirova K., Kharin A., Amirbek A. Forecasting the Regional Demand for Medical Workers in Kazakhstan: The Functional Principal Component Analysis Approach // Int J Environ Res Public Health. – 2025. – Vol. 22(7). – Article No. 1052. – DOI: https://doi.org/10.3390/ijerph22071052.
8. Liu J. X., Goryakin Y., Maeda A., Bruckner T., Scheffler R. Global Health Workforce Labor Market Projections for 2030 // Human Resources for Health. – 2017. – Vol. 15. – Article No. 11. – DOI: https://doi.org/10.1186/s12960-017-0187-2.
9. Asamani J. A., Bediako K. S. B., Boniol M., et al. Projected Health Workforce Requirements and Shortage for Addressing the Disease Burden in the WHO Africa Region, 2022–2030: A Needs-Based Modelling Study // BMJ Global Health. – 2024. – Vol. 9(10). – Article No. 015972. – DOI: https://doi.org/10.1136/bmjgh-2024-015972.
10. Xu T., Bos H., Byon E., Lavieri M. S., Renius K., Sweet B. V. Forecasting Hospital Drug Demand for Demand Patterns with Changepoints // IISE Transactions on Healthcare Systems Engineering. – 2025. – Vol. 15(3). – P. 269-286. – DOI: https://doi.org/10.1080/24725579.2025.2538009.
11. Lee J. T., Crettenden I., Tran M., Miller D., Cormack M., Cahill M., Li J., Sugiura T., Xiang F. Methods for Health Workforce Projection Model: Systematic Review and Recommended Good Practice Reporting Guideline // Hum Resour Health. – 2024. – Vol. 22(1). – Article No. 25. – DOI: https://doi.org/10.1186/s12960-024-00895-z.
12. Kharin A., Koichubekov B., Omarkulov B., Sorokina M., Korshukov I., Omarbekova N. First Steps in Forecasting the Health Workforce in Kazakhstan: A Baseline Scenario // J Clin Med Kaz. – 2021. – Vol. 18(3). – P. 40-45. – DOI: https://doi.org/10.23950/jcmk/10980.
13. Eyles E., Redaniel M. T., Jones T., Prat M., Keen T. Can We Accurately Forecast Non-Elective Bed Occupancy and Admissions in the NHS? A Time-Series MSARIMA Analysis of Longitudinal Data from an NHS Trust // BMJ Open. – 2022. – Vol. 12(4). – Article No. e056523. – DOI: https://doi.org/10.1136/bmjopen-2021-056523.
14. Patel I., Rahimi I. AI-Based Demand Forecasting and Load Balancing for Optimising Energy Use in Healthcare Systems: A Real Case Study // Systems. – 2026. – Vol. 14(1). – Article No. 94. – DOI: https://doi.org/10.3390/systems14010094.

15. Borges D., Nascimento M. C. V. COVID-19 ICU Demand Forecasting: A Two-Stage Prophet-LSTM Approach // Appl Soft Comput. – 2022. – Vol. 125. – Article No. 109181. – DOI: https://doi.org/10.1016/j.asoc.2022.109181.
16. Nover J., Bai M., Tismina P., Raut G., Patel D., Nadkarni G. N., Abella B. S., Klang E., Freeman R. Comparing Machine Learning and Nurse Predictions for Hospital Admissions in a Multisite Emergency Care System // medRxiv. – 2025. – DOI: https://doi.org/10.1101/2025.04.07.25325126.
17. King Z., Farrington J., Utley M., et al. Machine Learning for Real-Time Aggregated Prediction of Hospital Admission for Emergency Patients // npj Digital Medicine. – 2022. – Vol. 5. – Article No. 104. – DOI: https://doi.org/10.1038/s41746-022-00649-y.
18. Agius S., Cassar V., Magri C., Khan W., Obe D. A., Caruana G., Topham L. Predicting Emergency Severity Index (ESI) Level, Hospital Admission, and Admitting Ward in an Emergency Department Using Data-Driven Machine Learning // BMC Med Inform Decis Mak. – 2025. – Vol. 25(1). – Article No. 281. – DOI: https://doi.org/10.1186/s12911-025-02941-9.
19. Chen X., Lu G., Zhang H., Wan J. Knowledge Graph-Enhanced Deep Learning for Pharmaceutical Demand Forecasting // Sci Rep. – 2026. – Vol. 16(1). – Article No. 4776. – DOI: https://doi.org/10.1038/s41598-026-35113-4.
20. Yang C., Delcher C., Shenkman E., Ranka S. Machine Learning Approaches for Predicting High Cost High Need Patient Expenditures in Health Care // BioMedical Engineering OnLine. – 2018. – Vol. 17(Suppl. 1). – Article No. 131. – DOI: https://doi.org/10.1186/s12938-018-0568-3.
21. Taloba A. I., Abd El-Aziz R. M., Alshanbari H. M., El-Bagoury A. H. Estimation and Prediction of Hospitalization and Medical Care Costs Using Regression in Machine Learning // Journal of Healthcare Engineering. – 2022. – Vol. 2022. – Article No. 7969220. – DOI: https://doi.org/10.1155/2022/7969220.
22. Silva G., Duarte L. S., Shirassu M. M., de Moraes M. A., Chiavegatto Filho A. D. P. Unsupervised Machine Learning to Support the Regionalization of Healthcare Management in Noncommunicable Diseases // SSRN Electronic Journal. – 2024. – DOI: https://doi.org/10.2139/ssrn.4724314.
23. Neijzen D., Lunter G. Unsupervised Learning for Medical Data: A Review of Probabilistic Factorization Methods // Stat Med. – 2023. – Vol. 42(30). – P. 5541-5554. – DOI: https://doi.org/10.1002/sim.9924.
24. Kolyshkina I., Simoff S. Interpretability of Machine Learning Solutions in Public Healthcare: The CRISP-ML Approach // Front Big Data. – 2021. – Vol. 4. – Article No. 660206. – DOI: https://doi.org/10.3389/fdata.2021.660206.
25. Ravaghi H., Goshtaei M. K., Mannion R., et al. Hospital Efficiency in the Eastern Mediterranean Region: A Systematic Review and Meta-Analysis // Front Public Health. – 2023. – Vol. 11. – Article No. 1085459. – DOI: https://doi.org/10.3389/fpubh.2023.1085459.
26. Alhumaidi N. H., et al. The Use of Machine Learning for Analyzing Real-World Data in Disease Prediction and Management: Systematic Review // JMIR Medical Informatics. – 2024. – Vol. 13. – DOI: https://doi.org/10.2196/68898.
27. Abdulazeem H., Whitelaw S., Schauberger G., Klug S. J. A Systematic Review of Clinical Health Conditions Predicted by Machine Learning Diagnostic and Prognostic Models Trained or Validated Using Real-World Primary Health Care Data // PLOS One. – 2023. – Vol. 18(9). – Article No. 0274276. – DOI: https://doi.org/10.1371/journal.pone.0274276.
28. Об утверждении Комплексного плана развития Алматинской агломерации на 2024–2028 годы [Электронный ресурс]: Постановление Правительства Республики Казахстан от 28 декабря 2023 года № 1226 // Информационно-правовая система нормативных правовых актов Республики Казахстан «Әділет». – 2023. – URL: https://adilet.zan.kz/rus/docs/P2300001226 (Accessed: 28.05.2026).
29. Об утверждении Концепции развития здравоохранения Республики Казахстан до 2026 года [Электронный ресурс]: Постановление Правительства Республики Казахстан от 24 ноября 2022 года № 945 // Информационно-правовая система нормативных правовых актов Республики Казахстан «Әділет». – 2022. – URL: https://adilet.zan.kz/rus/docs/P2200000945 (accessed: 28.05.2026).
30. Кодекс Республики Казахстан от 7 июля

2020 года № 360-VI «О здоровье народа и системе здравоохранения» [Электронный ресурс] // Информационно-правовая система нормативных правовых актов Республики Казахстан «Әділет». – 2020. – URL: https://adilet.zan.kz/rus/docs/K2000000360 (accessed: 28.05.2026).

31. Kozhekenova N, Moiynbayeva S, Jeremic D, Dinic M, Semenov P, Nurgaliyeva Z, Tolekova S, Miller A, Smasheva A, Milicevic MS. The burden of COVID-19 in primary care of Almaty, Kazakhstan, 2021-2022 // Scientific Reports. – 2025. – Vol. 15. – P. 5374. – https://doi.org/10.1038/s41598-025-89707-5

32. WHO Regional Office for Europe. Health Systems in Action 2024: Kazakhstan [Electronic resource] // European Observatory on Health Systems and Policies. – 2024. – URL: https://eurohealthobservatory.who.int/publications/i/health-systems-in-action-kazakhstan-2024 (Accessed: 28.05.2026).

33. CAREC Health Program. Kazakhstan Health Security and Health System Brief [Electronic resource] // CAREC Program. – 2024. – URL: https://health.carecprogram.org/wp-content/uploads/2024/04/country-brief_Kazakhstan_final_6-Feb-2023.pdf (Accessed: 28.05.2026).

34. Программа развития города Алматы до 2025 года и среднесрочные перспективы до 2030 года [Электронный ресурс] / Управление развития и стратегических исследований города Алматы. – Алматы, 2022. – URL: https://almatydc.kz/uploads/reports/38/file/programma-razvitiya-almaty-2025_rus_12-09.pdf (accessed: 28.05.2026).

35. Atun R., de Jongh T., Secci F., Ohiri K., Adeyi O. Integration of Targeted Health Interventions into Health Systems: A Conceptual Framework for Analysis // Health Policy Plan. – 2010. – Vol. 25(2). – P. 104-111. – DOI: https://doi.org/10.1093/heapol/czp055.

36. MacKenzie A., Tomblin Murphy G., Audas R. A Dynamic, Multi-Professional, Needs-Based Simulation Model to Inform Human Resources for Health Planning // Hum Resour Health. – 2019. – Vol. 17(1). – Article No. 42. – DOI: https://doi.org/10.1186/s12960-019-0376-2.

37. Aziz R., Kapilashrami A., Majdzadeh R. Exploring the Inequalities Experienced by Health and Care Workforce and Their Bases – A Scoping Review Protocol // PLoS One. – 2024. – Vol. 19(4). – Article No. 0302175. – DOI: https://doi.org/10.1371/journal.pone.0302175.

38. Kapilashrami A., Aziz R. Pandemic Preparedness with 20/20 Vision: Applying an Intersectional Equity Lens to Health Workforce Planning // Int J Health Plann Manage. – 2023. – Vol. 38(5). – P. 1117-1126. – DOI: https://doi.org/10.1002/hpm.3677.

39. Kazemian M., Abdi Z., Meskarpour-Amiri M. Forecasting Iran National Health Expenditures: General Model and Conceptual Framework // J Educ Health Promot. – 2022. – Vol. 11. – Article No. 87. – DOI: https://doi.org/10.4103/jehp.jehp_362_21.

40. Klazoglou P., Dritsakis N. Modeling and Forecasting of US Health Expenditures Using ARIMA Models // In: Tsounis N., Vlachvei A. (eds). Advances in Panel Data Analysis in Applied Economic Research. ICOAE 2017. Springer Proceedings in Business and Economics. – Cham: Springer, 2018. – DOI: https://doi.org/10.1007/978-3-319-70055-7_36.

41. Wang J., Qin Z., Hsu J., Zhou B. A Fusion of Machine Learning Algorithms and Traditional Statistical Forecasting Models for Analyzing American Healthcare Expenditure // Healthcare Analytics. – 2024. – Vol. 5. – Article No. 100312. – DOI: https://doi.org/10.1016/j.health.2024.100312.

42. Lee J. T., Yeh M. H., Li V. C., Chen H. H., Liu Y. H., Chen Y. C., Wu D. B. Comparing Deep Learning and Classical Regression Approaches for Predicting Healthcare Expenditure and Spending: A Systematic Review // J Med Econ. – 2026. – Vol. 29(1). – P. 654-671. – DOI: https://doi.org/10.1080/13696998.2026.2630598.

43. Rathipriya R., Abdul Rahman A. A., Dhamodharavadhani S., Meero A., Yoganandan G. Demand Forecasting Model for Time-Series Pharmaceutical Data Using Shallow and Deep Neural Network Model // Neural Comput Appl. – 2023. – Vol. 35(2). – P. 1945-1957. – DOI: https://doi.org/10.1007/s00521-022-07889-9.

44. Ramadhan W., Noersasongko E., Syukur A., Soeleman M. Machine Learning Approaches for Pharmaceutical Demand Forecasting: A Bibliometric and Systematic Review of Methods and Research Trends // Ingénierie des Systèmes d'Information. – 2026. – Vol. 31(1). – P. 179-191. – DOI: https://doi.org/10.18280/isi.310117.

45. Baru R. A. A Decision Support Simulation Model for Bed Management in Healthcare [Master's thesis]. – Missouri University of Science and Technology, 2015. – URL: https://scholarsmine.mst.edu/masters_theses/7460/ (Accessed: 29.05.2026).
46. Peláez-Rodríguez C., Torres-López R., Pérez-Aracil J., López-Laguna N., Sánchez-Rodríguez S., Salcedo-Sanz S. An Explainable Machine Learning Approach for Hospital Emergency Department Visits Forecasting Using Continuous Training and Multi-Model Regression // Comput Methods Programs Biomed. – 2024. – Vol. 245. – Article No. 108033. – DOI: https://doi.org/10.1016/j.cmpb.2024.108033.
47. OECD. Health at a Glance 2025: OECD Indicators [Electronic resource]. – Paris: OECD Publishing, 2025. – DOI: https://doi.org/10.1787/8f9e3f98-en.
48. Alluhidan M., Tashkandi N., Alblowi F., et al. Challenges and Policy Opportunities in Nursing in Saudi Arabia // Hum Resour Health. – 2020. – Vol. 18. – Article No. 98. – DOI: https://doi.org/10.1186/s12960-020-00535-2.
49. Gailey S., Bruckner T. A., Lin T. K., et al. A Needs-Based Methodology to Project Physicians and Nurses to 2030: The Case of the Kingdom of Saudi Arabia // Hum Resour Health. – 2021. – Vol. 19. – Article No. 55. – DOI: https://doi.org/10.1186/s12960-021-00597-w.
50. Orhan F., Kurutkan M. N. Predicting Total Healthcare Demand Using Machine Learning: Separate and Combined Analysis of Predisposing, Enabling, and Need Factors // BMC Health Serv Res. – 2025. – Vol. 25. – Article No. 366. – DOI: https://doi.org/10.1186/s12913-025-12502-5.
51. Harrou F., Dairi A., Kadri F., Sun Y. Effective Forecasting of Key Features in Hospital Emergency Department: Hybrid Deep Learning-Driven Methods // Machine Learning with Applications. – 2022. – Vol. 7. – Article No. 100200. – DOI: https://doi.org/10.1016/j.mlwa.2021.100200.
52. Pan P., Yan R. Forecast Analysis of Shanghai Medical Service Demand Based on ARIMA Model // Sci Rep. – 2026. – DOI: https://doi.org/10.1038/s41598-026-47940-6.
53. Agius S., Cassar V., Magri C., Khan W., Obe D. A., Caruana G., Topham L. Predicting Emergency Severity Index (ESI) Level, Hospital Admission, and Admitting Ward in an Emergency Department Using Data-Driven Machine Learning // BMC Med Inform Decis Mak. – 2025. – Vol. 25. – Article No. 281. – DOI: https://doi.org/10.1186/s12911-025-02941-9.
54. Shafiekhani S., Namdar P., Rafiei S. COVID-19 Forecasting System for Hospital Needs Using ANFIS and LSTM Models: A Graphical User Interface Unit // Digital Health. – 2022. – Vol. 8. – Article No. 20552076221085057. – DOI: https://doi.org/10.1177/20552076221085057.
55. Yang Y., Qian Z., Zhuang X., et al. LSTM Model-Based Method for Forecasting the Demand of Medical Consumables // China Medical Devices. – 2022. – Vol. 37(6). – P. 123-126. – DOI: https://doi.org/10.3969/j.issn.1674-1633.2022.06.029.
56. Schilling M., Rickmann L., Hutschenreuter G., Spreckelsen C. Reduction of Platelet Outdating and Shortage by Forecasting Demand with Statistical Learning and Deep Neural Networks: Modeling Study // JMIR Med Inform. – 2022. – Vol. 10(2). – Article No. 29978. – DOI: https://doi.org/10.2196/29978.
57. Langenberger B., Schulte T., Groene O. The Application of Machine Learning to Predict High-Cost Patients: A Performance-Comparison of Different Models Using Healthcare Claims Data // PLOS One. – 2023. – Vol. 18(1). – Article No. 0279540. – DOI: https://doi.org/10.1371/journal.pone.0279540.

References

1. United Nations, Department of Economic and Social Affairs, Population Division. (2019). World urbanization prospects: The 2018 revision (ST/ESA/SER.A/420). United Nations. Retrieved May 15, 2026, from https://population.un.org/wup/Publications/Files/WUP2018-Report.pdf.
2. National Statistics Bureau of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan. (n.d.). Almaty city. Retrieved May 15, 2026, from https://stat.gov.kz.
3. Eurasian Research Institute. (2021). Urban demographics in Kazakhstan and economic significance of large cities. Akhmet Yassawi University. Retrieved May 15, 2026, from https://www.eurasian-research.org/publication/urban-demographics-in-kazakhstan-and-economic-significance-of-large-cities/ .
4. Government of the Republic of Kazakhstan. (2016). On the approval of the interregional

territorial development plan for the Almaty agglomeration: Resolution No. 302 of May 24, 2016. Adilet Information and Legal System. Retrieved May 15, 2026, from https://adilet.zan.kz/rus/docs/P1600000302.

5. Shaltynov, A., Abenova, M., Baibussinova, A., Semenova, Y., Omarov, N., Tanatarova, G., Sepbossynova, A., & Rocha, J. (2025). Inequality in the distribution and utilization of healthcare resources in Kazakhstan (2002–2023): A spatiotemporal analysis. Healthcare, 13(23), 3045. DOI: https://doi.org/10.3390/healthcare13233045.

6. Koichubekov, B., Begaidarova, R., Omarbekova, N., Mukhanova, M., Abdikadirova, K., Kharin, A., & Omarkulov, B. (2025). Forecasting the impact of Kazakhstan population growth on healthcare doctors demand. BMC Health Services Research, 25(1), 1456. DOI: https://doi.org/10.1186/s12913-025-13638-0.

7. Koichubekov, B., Omarkulov, B., Omarbekova, N., Abdikadirova, K., Kharin, A., & Amirbek, A. (2025). Forecasting the regional demand for medical workers in Kazakhstan: The functional principal component analysis approach. International Journal of Environmental Research and Public Health, 22(7), 1052. DOI: https://doi.org/10.3390/ijerph22071052.

8. Liu, J. X., Goryakin, Y., Maeda, A., Bruckner, T., & Scheffler, R. (2017). Global health workforce labor market projections for 2030. Human Resources for Health, 15, 11. DOI: https://doi.org/10.1186/s12960-017-0187-2.

9. Asamani, J. A., Bediako, K. S. B., Boniol, M., et al. (2024). Projected health workforce requirements and shortage for addressing the disease burden in the WHO Africa region, 2022–2030: A needs-based modelling study. BMJ Global Health, 9(10), e015972. DOI: https://doi.org/10.1136/bmjgh-2024-015972.

10. Xu, T., Bos, H., Byon, E., Lavieri, M. S., Renius, K., & Sweet, B. V. (2025). Forecasting hospital drug demand for demand patterns with changepoints. IISE Transactions on Healthcare Systems Engineering, 15(3), 269-286. DOI: https://doi.org/10.1080/24725579.2025.2538009.

11. Lee, J. T., Crettenden, I., Tran, M., Miller, D., Cormack, M., Cahill, M., Li, J., Sugiura, T., & Xiang, F. (2024). Methods for health workforce projection model: Systematic review and recommended good practice reporting guideline. Human Resources for Health, 22(1), 25. DOI: https://doi.org/10.1186/s12960-024-00895-z.

12. Kharin, A., Koichubekov, B., Omarkulov, B., Sorokina, M., Korshukov, I., & Omarbekova, N. (2021). First steps in forecasting the health workforce in Kazakhstan: A baseline scenario. Journal of Clinical Medicine of Kazakhstan, 18(3), 40–45. DOI: https://doi.org/10.23950/jcmk/10980.

13. Eyles, E., Redaniel, M. T., Jones, T., Prat, M., & Keen, T. (2022). Can we accurately forecast non-elective bed occupancy and admissions in the NHS? A time-series MSARIMA analysis of longitudinal data from an NHS trust. BMJ Open, 12(4), e056523. DOI: https://doi.org/10.1136/bmjopen-2021-056523.

14. Patel, I., & Rahimi, I. (2026). AI-based demand forecasting and load balancing for optimising energy use in healthcare systems: A real case study. Systems, 14(1), 94. DOI: https://doi.org/10.3390/systems14010094.

15. Borges, D., & Nascimento, M. C. V. (2022). COVID-19 ICU demand forecasting: A two-stage Prophet-LSTM approach. Applied Soft Computing, 125, 109181. DOI: https://doi.org/10.1016/j.asoc.2022.109181.

16. Nover, J., Bai, M., Tismina, P., Raut, G., Patel, D., Nadkarni, G. N., Abella, B. S., Klang, E., & Freeman, R. (2025). Comparing machine learning and nurse predictions for hospital admissions in a multisite emergency care system. medRxiv. DOI: https://doi.org/10.1101/2025.04.07.25325126.

17. King, Z., Farrington, J., Utley, M., et al. (2022). Machine learning for real-time aggregated prediction of hospital admission for emergency patients. npj Digital Medicine, 5, 104. DOI: https://doi.org/10.1038/s41746-022-00649-y.

18. Agius, S., Cassar, V., Magri, C., Khan, W., Obe, D. A., Caruana, G., & Topham, L. (2025). Predicting emergency severity index (ESI) level, hospital admission, and admitting ward in an emergency department using data-driven machine learning. BMC Medical Informatics and Decision Making, 25(1), 281. DOI: https://doi.org/10.1186/s12911-025-02941-9.

19. Chen, X., Lu, G., Zhang, H., & Wan, J. (2026). Knowledge graph-enhanced deep learning for pharmaceutical demand forecasting. Scientific Reports, 16(1), 4776. DOI: https://doi.org/10.1038/s41598-026-35113-4.

20. Yang, C., Delcher, C., Shenkman, E., & Ranka,

S. (2018). Machine learning approaches for predicting high cost high need patient expenditures in health care. BioMedical Engineering OnLine, 17(Suppl. 1), 131. DOI: https://doi.org/10.1186/s12938-018-0568-3.

21. Taloba, A. I., Abd El-Aziz, R. M., Alshanbari, H. M., & El-Bagoury, A. H. (2022). Estimation and prediction of hospitalization and medical care costs using regression in machine learning. Journal of Healthcare Engineering, 2022, Article 7969220. DOI: https://doi.org/10.1155/2022/7969220.

22. Silva, G., Duarte, L. S., Shirassu, M. M., de Moraes, M. A., & Chiavegatto Filho, A. D. P. (2024). Unsupervised machine learning to support the regionalization of healthcare management in noncommunicable diseases. SSRN Electronic Journal. DOI: https://doi.org/10.2139/ssrn.4724314.

23. Neijzen, D., & Lunter, G. (2023). Unsupervised learning for medical data: A review of probabilistic factorization methods. Statistics in Medicine, 42(30), 5541-5554. DOI: https://doi.org/10.1002/sim.9924.

24. Kolyshkina, I., & Simoff, S. (2021). Interpretability of machine learning solutions in public healthcare: The CRISP-ML approach. Frontiers in Big Data, 4, 660206. DOI: https://doi.org/10.3389/fdata.2021.660206.

25. Ravaghi, H., Goshtaei, M. K., Mannion, R., et al. (2023). Hospital efficiency in the Eastern Mediterranean region: A systematic review and meta-analysis. Frontiers in Public Health, 11, 1085459. DOI: https://doi.org/10.3389/fpubh.2023.1085459.

26. Alhumaidi, N. H., et al. (2024). The use of machine learning for analyzing real-world data in disease prediction and management: Systematic review. JMIR Medical Informatics, 13. DOI: https://doi.org/10.2196/68898.

27. Abdulazeem, H., Whitelaw, S., Schauberger, G., & Klug, S. J. (2023). A systematic review of clinical health conditions predicted by machine learning diagnostic and prognostic models trained or validated using real-world primary health care data. PLOS ONE, 18(9), 0274276. DOI: https://doi.org/10.1371/journal.pone.0274276.

28. Pravitel'stvo Respubliki Kazakhstan. (2023). Ob utverzhdenii Kompleksnogo plana razvitiya Almatinskoi aglomeratsii na 2024–2028 gody: Postanovlenie Pravitel'stva Respubliki Kazakhstan ot 28 dekabrya 2023 goda No. 1226. Adilet Information and Legal System of Normative Legal Acts of the Republic of Kazakhstan. Retrieved May 28, 2026, from https://adilet.zan.kz/rus/docs/P2300001226 (in Russian).

29. Pravitel'stvo Respubliki Kazakhstan. (2022). Ob utverzhdenii Kontseptsii razvitiya zdravookhraneniya Respubliki Kazakhstan do 2026 goda: Postanovlenie Pravitel'stva Respubliki Kazakhstan ot 24 noyabrya 2022 goda No. 945. Adilet Information and Legal System of Normative Legal Acts of the Republic of Kazakhstan. Retrieved May 28, 2026, from https://adilet.zan.kz/rus/docs/P2200000945 (in Russian).

30. Respublika Kazakhstan. (2020). Kodeks Respubliki Kazakhstan ot 7 iyulya 2020 goda No. 360-VI "O zdorov'e naroda i sisteme zdravookhraneniya". Adilet Information and Legal System of Normative Legal Acts of the Republic of Kazakhstan. Retrieved May 28, 2026, from https://adilet.zan.kz/rus/docs/K2000000360 (in Russian).

31. Kozhekenova, N., Moiynbayeva, S., Jeremic, D., Dinic, M., Semenov, P., Nurgaliyeva, Z., Tolekova, S., Miller, A., Smasheva, A., & Milicevic, M. S. (2025). The burden of COVID-19 in primary care of Almaty, Kazakhstan, 2021-2022. Scientific Reports, 15, 5374. https://doi.org/10.1038/s41598-025-89707-5.

32. World Health Organization Regional Office for Europe. (2024). Health systems in action 2024: Kazakhstan. European Observatory on Health Systems and Policies. Retrieved May 28, 2026, from https://eurohealthobservatory.who.int/publications/i/health-systems-in-action-kazakhstan-2024.

33. CAREC Health Program. (2024). Kazakhstan health security and health system brief. Retrieved April 28, 2026, from https://health.carecprogram.org/wp-content/uploads/2024/04/country-brief_Kazakhstan_final_6-Feb-2023.pdf.

34. Upravlenie razvitiya i strategicheskikh issledovanii goroda Almaty. (2022). Almaty city development program until 2025 and medium-term prospects until 2030. Retrieved May 28, 2026, from https://almatydc.kz/uploads/reports/38/file/programma-razvitiya-almaty-2025_rus_12-09.pdf (in Russian).

35. Atun, R., de Jongh, T., Secci, F., Ohiri, K., & Adeyi, O. (2010). Integration of targeted health interventions into health systems: A conceptual

framework for analysis. Health Policy and Planning, 25(2), 104-111. DOI: https://doi.org/10.1093/heapol/czp055.

36. MacKenzie, A., Tomblin Murphy, G., & Audas, R. (2019). A dynamic, multi-professional, needs-based simulation model to inform human resources for health planning. Human Resources for Health, 17(1), 42. DOI: https://doi.org/10.1186/s12960-019-0376-2.

37. Aziz, R., Kapilashrami, A., & Majdzadeh, R. (2024). Exploring the inequalities experienced by health and care workforce and their bases: A scoping review protocol. PLOS ONE, 19(4), 0302175. DOI: https://doi.org/10.1371/journal.pone.0302175.

38. Kapilashrami, A., & Aziz, R. (2023). Pandemic preparedness with 20/20 vision: Applying an intersectional equity lens to health workforce planning. International Journal of Health Planning and Management, 38(5), 1117-1126. DOI: https://doi.org/10.1002/hpm.3677.

39. Kazemian, M., Abdi, Z., & Meskarpour-Amiri, M. (2022). Forecasting Iran national health expenditures: General model and conceptual framework. Journal of Education and Health Promotion, 11, 87. DOI: https://doi.org/10.4103/jehp.jehp_362_21.

40. Klazoglou, P., & Dritsakis, N. (2018). Modeling and forecasting of US health expenditures using ARIMA models. In N. Tsounis & A. Vlachvei (Eds.), Advances in panel data analysis in applied economic research (Springer Proceedings in Business and Economics). Springer. DOI: https://doi.org/10.1007/978-3-319-70055-7_36.

41. Wang, J., Qin, Z., Hsu, J., & Zhou, B. (2024). A fusion of machine learning algorithms and traditional statistical forecasting models for analyzing American healthcare expenditure. Healthcare Analytics, 5, 100312. DOI: https://doi.org/10.1016/j.health.2024.100312.

42. Lee, J. T., Yeh, M. H., Li, V. C., Chen, H. H., Liu, Y. H., Chen, Y. C., & Wu, D. B. (2026). Comparing deep learning and classical regression approaches for predicting healthcare expenditure and spending: A systematic review. Journal of Medical Economics, 29(1), 654-671. DOI: https://doi.org/10.1080/13696998.2026.2630598.

43. Rathipriya, R., Abdul Rahman, A. A., Dhamodharavadhani, S., Meero, A., & Yoganandan, G. (2023). Demand forecasting model for time-series pharmaceutical data using shallow and deep neural network model. Neural Computing and Applications, 35(2), 1945-1957. DOI: https://doi.org/10.1007/s00521-022-07889-9.

44. Ramadhan, W., Noersasongko, E., Syukur, A., & Soeleman, M. (2026). Machine learning approaches for pharmaceutical demand forecasting: A bibliometric and systematic review of methods and research trends. Ingénierie des Systèmes d'Information, 31(1), 179-191. DOI: https://doi.org/10.18280/isi.310117.

45. Baru, R. A. (2015). A decision support simulation model for bed management in healthcare (Master's thesis, Missouri University of Science and Technology). Retrieved May 29, 2026, from https://scholarsmine.mst.edu/masters_theses/7460/.

46. Peláez-Rodríguez, C., Torres-López, R., Pérez-Aracil, J., López-Laguna, N., Sánchez-Rodríguez, S., & Salcedo-Sanz, S. (2024). An explainable machine learning approach for hospital emergency department visits forecasting using continuous training and multi-model regression. Computer Methods and Programs in Biomedicine, 245, 108033. DOI: https://doi.org/10.1016/j.cmpb.2024.108033.

47. OECD. (2025). Health at a glance 2025: OECD indicators. OECD Publishing. DOI: https://doi.org/10.1787/8f9e3f98-en.

48. Alluhidan, M., Tashkandi, N., Alblowi, F., et al. (2020). Challenges and policy opportunities in nursing in Saudi Arabia. Human Resources for Health, 18, 98. DOI: https://doi.org/10.1186/s12960-020-00535-2.

49. Gailey, S., Bruckner, T. A., Lin, T. K., et al. (2021). A needs-based methodology to project physicians and nurses to 2030: The case of the Kingdom of Saudi Arabia. Human Resources for Health, 19, 55. DOI: https://doi.org/10.1186/s12960-021-00597-w.

50. Orhan, F., & Kurutkan, M. N. (2025). Predicting total healthcare demand using machine learning: Separate and combined analysis of predisposing, enabling, and need factors. BMC Health Services Research, 25, 366. DOI: https://doi.org/10.1186/s12913-025-12502-5.

51. Harrou, F., Dairi, A., Kadri, F., & Sun, Y. (2022). Effective forecasting of key features in hospital emergency department: Hybrid deep learning-driven methods. Machine Learning with Applications, 7, 100200. DOI: https://doi.org/10.1016/j.mlwa.2021.100200.

52. Pan, P., & Yan, R. (2026). Forecast analysis of Shanghai medical service demand based on ARIMA model. Scientific Reports. DOI: https://doi.org/10.1038/s41598-026-47940-6.
53. Agius, S., Cassar, V., Magri, C., Khan, W., Obe, D. A., Caruana, G., & Topham, L. (2025). Predicting emergency severity index (ESI) level, hospital admission, and admitting ward in an emergency department using data-driven machine learning. BMC Medical Informatics and Decision Making, 25, 281. DOI: https://doi.org/10.1186/s12911-025-02941-9.
54. Shafiekhani, S., Namdar, P., & Rafiei, S. (2022). COVID-19 forecasting system for hospital needs using ANFIS and LSTM models: A graphical user interface unit. Digital Health, 8, 20552076221085057. DOI: https://doi.org/10.1177/20552076221085057.
55. Yang, Y., Qian, Z., Zhuang, X., et al. (2022). LSTM model-based method for forecasting the demand of medical consumables. China Medical Devices, 37(6), 123-126. DOI: https://doi.org/10.3969/j.issn.1674-1633.2022.06.029.
56. Schilling, M., Rickmann, L., Hutschenreuter, G., & Spreckelsen, C. (2022). Reduction of platelet outdating and shortage by forecasting demand with statistical learning and deep neural networks: Modeling study. JMIR Medical Informatics, 10(2), 29978. DOI: https://doi.org/10.2196/29978.
57. Langenberger, B., Schulte, T., & Groene, O. (2023). The application of machine learning to predict high-cost patients: A performance-comparison of different models using healthcare claims data. PLOS ONE, 18(1), 0279540. DOI: https://doi.org/10.1371/journal.pone.0279540.

ҚАЛАЛЫҚ АГЛОМЕРАЦИЯЛАРДАҒЫ ДЕНСАУЛЫҚ САҚТАУ РЕСУРСТАРЫН БОЛЖАУ МОДЕЛЬДЕРІ МЕН ӘДІСТЕРІ: ӘДЕБИ ШОЛУ

Ж. Б. Ағманова[1]*, Ж. А. Калматаева[1], К. К. Тогузбаева[1], Г. Д. Искакова[2], С. Е. Султангазиева[1]

[1] «С. Д. Асфендияров атындағы Қазақ Ұлттық медицина университеті» КЕАҚ, Қазақстан, Алматы

[2] «Салидат Қайырбекова атындағы Ұлттық ғылыми денсаулық сақтауды дамыту орталығы» ШЖҚ РМК, Қазақстан, Алматы

**Корреспондент автор*

Аңдатпа

Өзектілігі. Қалалық агломерациялардағы халық саны өсуі денсаулық сақтау қызметіне сұраныс пен оның кадрлық, дәрілік, қаржылық және материалдық-техникалық ресурстармен қамтамасыз етілуі арасындағы өлшенетін алшақтықты тудырады. Алматы агломерациясында шамамен 3,5 миллион тұрғын шоғырланған, ал 2030 жылға қарай олардың саны 4,5 миллионға жетеді деп болжанып отыр. Қазақстан Республикасы Денсаулық сақтау министрлігінің мәліметтері бойынша 2023 жылы дәрігерлер тапшылығы 4 864 толық уақыттық лауазымды құрады, ал қосарлас жұмыс істеу коэффициенті 1,4-ке жетіп, медициналық қызметкерлердің жүйелі шамадан тыс жүктемесін көрсетті.

Мақсаты. Қалалық агломерациялардағы денсаулық сақтау ресурстарына деген қажеттілікті болжаудың қазіргі модельдерін, әсіресе машинамен оқыту құралдарын талдау және олардың Алматы агломерациясының жағдайына қолдану мүмкіндігін бағалау.

Материал және әдістер. 2010 жылғы қаңтардан 2026 жылғы наурызға дейінгі кезеңде PubMed, Scopus, Web of Science Core Collection және WHO IRIS дерекқорларында әдебиет іздеу жүргізілді. Шолуға дәлдігін бағалайтын сандық болжамды модельдерді қамтитын түпнұсқа зерттеулер, жүйелі шолулар және WHO/OECD әдістемелік есептері енгізілді (MAE, RMSE, MAPE, AUROC, R^2) қалалық агломерациялар немесе урбанизация деңгейі ≥ 50 % аймақтар бойынша дәлдігін бағалайтын сандық болжамды модельдерді қамтитын түпнұсқа зерттеулер, жүйелі шолулар және ДДҰ/ЭЫДҰ әдістемелік есептері қарастырылды. Анықталған 1 286 жазбаның ішінен шолуға 57 басылым енгізілді.

Нәтижелер. Статистикалық модельдер ең көп тараған (40,4 %), одан кейін бақылаумен жүргізілетін машиналық оқыту әдістері (34,0 %) және гибридті модельдер (17,0 %) келді; бақылаусыз машиналық оқыту әдістері тек 4 басылымда (8,5 %) қолданылды. Тек 3 модель (6,4 %) Қазақстандағы деректер негізінде тексерілген және тек адам ресурстары санатын қамтиды. Ешбір модель барлық төрт ресурс санатын бір уақытта қамтымайды.

Қорытындылар. Осы шолудың методологиялық нәтижелері ұлттық жоспарлау құжаттарына сәйкес кемінде үш ресурс санатын қамтитын және болжау мерзімі 5–10 жылды құрайтын қадағаланбайтын машинамен оқытуға негізделген біріктірілген болжау моделін әзірлеуді негіздейді.

***Түйін сөздер**: денсаулық сақтау ресурстары, болжамдық модель, машиналық оқыту, мұғалімсіз оқыту, қалалық агломерация, жүйелі шолу, Қазақстан, медициналық кадрлар.*

МОДЕЛИ И МЕТОДЫ ПРОГНОЗИРОВАНИЯ РЕСУРСОВ ЗДРАВООХРАНЕНИЯ В ГОРОДСКИХ АГЛОМЕРАЦИЯХ: ЛИТЕРАТУРНЫЙ ОБЗОР

Ж. Б. Агманова[1]*, Ж. А. Калматаева[1], К. К. Тогузбаева[1], Г. Д. Искакова[2], С. Е. Султангазиева[1]

[1] НАО «Казахский национальный медицинский университет имени С. Д. Асфендиярова», Казахстан, Алматы

[2] РГП на ПХВ «Национальный научный центр развития здравоохранения имени Салидат Каирбековой», Казахстан, Алматы

**Корреспондирующий автор*

Аннотация

Актуальность. Рост населения в городских агломерациях создаёт количественно измеримый разрыв между спросом на медицинскую помощь и обеспеченностью кадровыми, лекарственными, финансовыми и материально-техническими ресурсами. Алматинская агломерация концентрирует около 3,5 миллиона жителей с прогнозируемым ростом до 4,5 миллиона человек к 2030 году. По данным Министерства здравоохранения Республики Казахстан, в 2023 году дефицит врачей составил 4 864 ставки, а коэффициент совместительства достиг 1,4, что отражает системную перегрузку кадров.

Цель. Анализ современных моделей прогнозирования потребности в ресурсах здравоохранения в городских агломерациях с фокусом на инструментах машинного обучения, их оценки применимости к условиям Алматинской агломерации.

Материал и методы: Поиск литературы был проведен в базах данных PubMed, Scopus, Web of Science Core Collection, WHO IRIS за период с января 2010 года по март 2026 года. В обзор включались оригинальные исследования, систематические обзоры и методологические отчёты ВОЗ/ОЭСР, содержащие количественные прогностические модели с оценкой точности (MAE, RMSE, MAPE, AUROC, R^2) на уровне городских агломераций или регионов с уровнем урбанизации ≥ 50 %. Из 1 286 идентифицированных записей в обзор включены 57 публикаций.

Результаты. Статистические модели были наиболее распространены (40,4 %), затем методы машинного обучения с учителем (34,0 %), гибридные модели (17,0 %), методы машинного обучения без учителя - лишь в 4 публикациях (8,5 %). Только 3 модели (6,4 %) валидированы на данных Казахстана и охватывают исключительно категорию кадровых ресурсов. Ни одна модель не охватывает одновременно все четыре категории ресурсов.

Выводы. Методологические данные обзора обосновывают разработку интегрированной модели прогнозирования на основе машинного обучения без учителя для Алматинской агломерации с охватом не менее трёх категорий ресурсов и горизонтом прогноза 5-10 лет в соответствии с национальными плановыми документами.

***Ключевые слова**: ресурсы здравоохранения, прогностическая модель, машинное обучение, обучение без учителя, городская агломерация, систематический обзор, Казахстан, медицинские кадры.*

АВТОРЛАР ТУРАЛЫ

Ағманова Жанат Болатқызы – С. Д. Асфендияров атындағы Қазақ Ұлттық медицина университетінің 2-курс докторанты, Қазақстан, Алматы; тел: +7 707 970 70 78; e-mail: Jan-janetta@mail.ru; ORCID: https://orcid.org/0009-0001-7018-4154

Калматаева Жанна Амантаевна – С. Д. Асфендияров атындағы Қазақ Ұлттық медицина университетінің академиялық қызмет жөніндегі проректоры, медицина ғылымдарының докторы, профессор, Қазақстан, Алматы; e-mail: kalmatayeva.z@kaznmu.kz; ORCID: https://orcid.org/0000-0002-5562-1969

Тогузбаева Карлыгаш Кабдешовна – С. Д. Асфендияров атындағы Қазақ Ұлттық медицина университетінің қоғамдық денсаулық сақтау кафедрасының профессоры, медицина ғылымдарының докторы, профессор, Қазақстан, Алматы; e-mail: toguzbaeva.k@kaznmu.kz; ORCID: https://orcid.org/0009-0000-2063-8114

Искакова Гульнара Долдашевна – Қазақстан Республикасы Денсаулық сақтау министрлігінің «Салидат Қайырбекова атындағы денсаулық сақтауды дамыту ұлттық ғылыми орталығы» шаруашылық жүргізу құқығындағы республикалық мемлекеттік кәсіпорнының Алматы облыстық филиалының басшысы, Қазақстан, Алматы; e-mail: omo_gkb7@mail.ru; ORCID: https://orcid.org/0000-0003-4861-0601

Султангазиева Светлана Елеусизовна – С. Д. Асфендияров атындағы Қазақ Ұлттық медицина университетінің клиникалық қызмет жөніндегі проректоры, медицина ғылымдарының кандидаты, Қазақстан, Алматы; e-mail: Sultangaziyeva.s@kaznmu.kz; ORCID: https://orcid.org/0009-0003-7169-1750

ОБ АВТОРАХ

Агманова Жанат Болатовна – докторант 2-го курса Казахского Национального медицинского университета имени С. Д. Асфендиярова, Казахстан, Алматы; тел.: +7 707 970 70 78; e-mail: Jan-janetta@mail.ru; ORCID: https://orcid.org/0009-0001-7018-4154

Калматаева Жанна Амантаевна – проректор по академической деятельности Казахского Национального медицинского университета имени С. Д. Асфендиярова, доктор медицинских наук, профессор, Казахстан, Алматы; e-mail: kalmatayeva.z@kaznmu.kz; ORCID: https://orcid.org/0000-0002-5562-1969

Тогузбаева Карлыгаш Кабдешовна – профессор кафедры общественного здравоохранения Казахского Национального медицинского университета имени С. Д. Асфендиярова, доктор медицинских наук, профессор, Казахстан, Алматы; e-mail: toguzbaeva.k@kaznmu.kz; ORCID: https://orcid.org/0009-0000-2063-8114

Искакова Гульнара Долдашевна – руководитель Алматинского областного филиала Республиканского государственного предприятия на праве хозяйственного ведения «Национальный научный центр развития здравоохранения имени Салидат Каирбековой» Министерства здравоохранения Республики Казахстан, Казахстан, Алматы; e-mail: omo_gkb7@mail.ru; ORCID: https://orcid.org/0000-0003-4861-0601

Султангазиева Светлана Елеусизовна – проректор по клинической деятельности Казахского Национального медицинского университета имени С. Д. Асфендиярова, кандидат медицинских наук, Казахстан, Алматы; e-mail: Sultangaziyeva.s@kaznmu.kz; ORCID: https://orcid.org/0009-0003-7169-1750

ABOUT AUTHORS

Agmanova Zhanat B. – 2nd-year PhD student, Asfendiyarov Kazakh National Medical University, Kazakhstan, Almaty; phone: +7 707 970 70 78, e-mail: Jan-janetta@mail.ru; ORCID: https://orcid.org/0009-0001-7018-4154

Kalmatayeva Zhanna A. – Vice-Rector for Academic Affairs, Doctor of Medical Sciences, Professor, Asfendiyarov Kazakh National Medical University, Kazakhstan, Almaty; e-mail: kalmatayeva.z@kaznmu.kz; ORCID: https://orcid.org/0000-0002-5562-1969

Karlygash K. Toguzbayeva – Professor of the Department of Public Health, Doctor of Medical Sciences, Professor, Asfendiyarov Kazakh National Medical University, Kazakhstan, Almaty; e-mail: toguzbaeva.k@kaznmu.kz; ORCID: https://orcid.org/0009-0000-2063-8114

Gulnara D. Iskakova – Head of the Almaty Regional Branch of the Salidat Kairbekova National Research Center for Health Development, Ministry of Healthcare of the Republic of Kazakhstan, Kazakhstan, Almaty; e-mail: omo_gkb7@mail.ru; ORCID: https://orcid.org/0000-0003-4861-0601

Svetlana Ye. Sultangaziyeva – Vice-Rector for Clinical Affairs, Candidate of Medical Sciences, Asfendiyarov Kazakh National Medical University, Kazakhstan, Almaty; e-mail: Sultangaziyeva.s@kaznmu.kz; ORCID: https://orcid.org/0009-0003-7169-1750

Authors' contribution. *Conceptualization: Zh. B. Agmanova, Zh. A. Kalmatayeva; Methodology: Zh. B. Agmanova, Zh. A. Kalmatayeva; Literature search and data extraction: Zh. B. Agmanova, G. D. Iskakova, S. E. Sultangaziyeva; Critical analysis and synthesis of the literature: Zh. B. Agmanova, K. K. Toguzbayeva, G. D. Iskakova; Writing – original draft preparation: Zh. B. Agmanova, Zh. A. Kalmatayeva, S. E. Sultangaziyeva; Writing – review and editing: Zh. A. Kalmatayeva, K. K. Toguzbayeva, G. D. Iskakova, S. E. Sultangaziyeva; Supervision: Zh. A. Kalmatayeva.*

Conflict of interest. *The authors declare no conflict of interest.*

Funding. *This research received no external funding.*

All authors have approved the final version of the article and are responsible for its content.

Article received: 18.05.2026 year.

Accepted for publication: 19.06.2026 year.