Applied Computer Science 2025, vol. 21, no. 2, pp. 82–95
https://doi.org/10.35784/acs_7418

Submitted: 2025-03-11 | Revised: 2025-04-29 | Accepted: 2025-05-09

Keywords: artificial neural network, decision making, digital healthcare, economics, telemedicine

Zhannur ABDRAKHMANOVA [1], *Talgat DEMESSINOV* [2*], *Kadisha JAPAROVA* [2], *Monika KULISZ* [3], *Gulzhan BAYTIKENOVA* [4], *Ainur KARIPOVA* [1], *Zhansaya ERSAINOVA* [4]

[1] L.N. Gumilyov Eurasian National University, Kazakhstan, abdrakhmanova.zhannur@inbox.ru, karipovaainur@mail.ru
[2] Sh. Ualikhanov Kokshetau University, Kazakhstan, demesinov73@list.ru, DKymarovna@shokan.edu.kz
[3] Lublin University of Technology, Poland, m.kulisz@pollub.pl
[4] D.Serikbayev East Kazakhstan Technical University, Kazakhstan, GBaytikenova@mail.ru, Zhansaya.ersayynova@mail.ru
[*] Corresponding author: demesinov73@list.ru

Predictive modeling of telemedicine implementation in central Asia using neural networks

Abstract

The rapid development of digital technologies has transformed healthcare systems around the world, and telemedicine has become the primary solution to problems related to the availability and quality of medical care. This study examines the adoption of telemedicine in five Central Asian countries - Kazakhstan, Kyrgyzstan, Uzbekistan, Tajikistan, and Turkmenistan - by modeling the relationship between key medical, demographic, and technological factors and the number of telemedicine users. To identify the factors that contribute to telemedicine adoption, a dataset of epidemiological, demographic, and digital infrastructure indicators was analyzed. For the analysis, data from the National Statistical Office of the Republic of Kazakhstan (2014-2024) were used. To predict the number of telemedicine users, an artificial neural network (ANN) was used, which has a shallow network structure with four input neurons representing the main predictors and one output neuron for potential telemedicine users. The predictive model showed excellent accuracy, as evidenced by a very strong correlation between predicted and observed values (R = 0.99245). In addition, the reliability of the model is confirmed by its low error rates, with a mean squared error (MSE) of 0.007 and a root mean squared error (RMSE) of 0.0839. These findings underscore the transformative potential of telemedicine to address health challenges in Central Asia, while providing valuable insights into the epidemiological, demographic, and technological drivers that can guide targeted policy initiatives and strategic investments in digital infrastructure.

1. INTRODUCTION

Several policies and innovations have advocated the shift to digital healthcare, especially during the COVID-19 pandemic, and have continued to evolve since then. Cheng and Yip (2024) stated that China's telemedicine and Internet healthcare model is exceptional because it has been led by private technology companies, which have developed and enhanced the digital health ecosystem and changed the way healthcare services are delivered. Since the 1980s, when information networks were established, China's Internet health industry has been on an upward trajectory since the 2010s, driven by partnerships with the e-commerce and logistics industries. A unique aspect of the Chinese model is the combination of public and private systems, where patients' telemedicine consultations with public hospital doctors take place on private, fully operational digital health service platforms (Cheng & Yip, 2024).

The importance of digital literacy in the health sector became increasingly evident following the educational efforts of organizations such as SIBIM, especially during and after the COVID-19 pandemic. The pandemic clearly highlighted the need for health professionals to be competent in digital tools and platforms. For example, Katsaliaki (2024) noted that the COVID-19 pandemic significantly increased the demand for healthcare providers skilled in telemedicine, biomedical informatics, and cloud communication systems. This development reflects a broader global trend, particularly in Europe, where the implementation of comprehensive eHealth policies has gained momentum. Furthermore, highlights how the coronavirus pandemic accelerated the digitization of government services in response to social distancing measures. These developments illustrate how COVID-19 acted as a global catalyst for the expansion and recognition of digital health, facilitating remote and effective healthcare delivery (Katsaliaki, 2024).

The importance of digitization in healthcare is paramount for Central Asian countries, where the incidence of noncommunicable diseases, such as stroke and metabolic diseases, continues to rise. Zhang et al. (2024) note that the burden of ischemic stroke, which is most often caused by metabolic processes, is relatively high, as this condition has been one of the leading causes of death and disability for many nations over time, and Central Asia is greatly affected by this due to the high hypertension risk population. To address this, there is a need for efficient and accessible healthcare systems that can anticipate and manage risks and provide remote care, highlighting the role of digital healthcare systems (Zhang et al., 2024).

There is potential for telemedicine, blockchain, and other digital tools to contribute to the transformation of healthcare systems. For example, Kuo et al. (2017) highlight the role of blockchain in securing data and automating key processes critical to telehealth applications. Their study of blockchain in long-term care reveals many opportunities for enhanced data control and streamlined service integration. However, it also raises concerns about technological readiness and stakeholder support. Acknowledging these challenges is essential as Central Asian countries explore digital health options for vast, often underserved regions (Kuo et al., 2017). Similarly, Kruse et al. (2016) highlight the need for significant investment in IT infrastructure and staff training to sustain digital health services. Their systematic review of telemedicine after surgery shows that remote monitoring can improve quality of care and reduce complications, but further efforts are needed to meet patient needs and ensure successful implementation (Kruse et al., 2016).

This study examines the status quo, benefits, and challenges of ICT in the health sector in Central Asia. This region has faced challenges in accessing healthcare services due to many geographical and infrastructural factors. It will also set the stage by identifying key assets and barriers that can be used to develop appropriate, targeted strategies for further embedding digital health systems into the fabric of the region. Modern technologies, such as artificial intelligence (AI), cloud computing, and blockchain, have established themselves in various sectors of the economy, including the healthcare industry, providing on-the-spot communication, health record storage, and forecasting. Introducing these technologies into Central Asia's healthcare system offers excellent opportunities to overcome time constraints, optimize processes, and improve the availability and standards of medical services.

The widespread use of artificial intelligence (AI) and machine learning technologies in healthcare has received a tremendous boost in recent years. These technologies play an important role in solving many problems, from medical diagnostics to patient monitoring, improved treatment methods, and effective resource management. Topol (2019) discusses the rapid development of artificial intelligence in healthcare, highlighting the potential of neural networks in diagnosis and treatment. In addition, Miotto et al. (2017) explore deep learning-based predictive models and demonstrate their promising applications in the medical field.

The benefits of using predictive models and neural networks in healthcare are clear. In their study, Rajkomar et al (2018) highlight the importance of machine learning techniques in predictive healthcare models. Many models based on these studies help improve the efficiency of medical data analysis and patient prediction systems. In addition, Beam and Kohane (2018) investigate the use of artificial intelligence and neural networks in healthcare, exploring their potential to improve diagnostic accuracy and enable personalized treatment.

Recent studies have also focused on the application of AI and ML in predicting treatment-seeking behavior for mental health conditions. A study by Younis (2024) examines the effectiveness of various machine learning classifiers, including random forest, gradient boosting, SVM, KNN, and logistic regression, in predicting a patient's willingness to seek treatment for mental illness. Using the Open Sourcing Mental Illness (OSMI) dataset, the study demonstrates the potential of AI in predicting patient behavior, with Random Forest and Gradient Boosting achieving the highest accuracy (0.81 and 0.83, respectively). These findings provide valuable insights into mental health treatment-seeking behavior and reinforce the role of AI in healthcare decision making.

The place and importance of telemedicine technologies in healthcare is growing every year. The development of this field in Central Asia, along with the potential opportunities, presents a number of difficulties. Bashshur et al. (2020) conducted a study on the global development of telemedicine and discussed the opportunities and limitations associated with telemedicine, particularly in regions with infrastructure and resource challenges similar to Central Asia. Similarly, Scott Kruse et al. (2017) examined the implementation of telemedicine in rural areas and identified practical strategies to overcome barriers with the aim of increasing the effectiveness and adoption of this system.

In addition to predictive models, security and data integrity remain critical aspects of digital health systems. Makhlouf et al. (2024) propose a biometric-based watermarking approach for medical image security in e-health systems, using patient palm print templates as watermarks. This technique, coupled with Lorenz chaotic mapping for watermark embedding, provides a high level of security and resistance to various attacks such as Gaussian noise, compression, and image rotations. The study reports an impressive true acceptance rate of 99.86%, highlighting its potential for protecting personal health information and ensuring secure data transmission in telemedicine environments.

Considering the use of artificial neural networks in healthcare, Jiang et al. (2017) discuss the role of AI and neural networks in healthcare decision making. They find that neural networks are an important component in the development of disease prediction and patient care systems. These studies provide effective approaches and innovations to expand the capabilities of neural networks in healthcare.

In Central Asia, many predictive models and methods are used to implement telemedicine and artificial neural networks. The results of various studies and experiments in this area show high efficiency. In their studies, Razzak et al. (2019) provide a broader understanding of the use of predictive models in healthcare and suggest ways to implement telemedicine and neural networks. In their recommendations, each researcher demonstrates how these technologies contribute to the effective management and improvement of healthcare systems.

Despite these extensive studies, however, there remains a significant research gap: no predictive model has yet been specifically tailored to account for the unique epidemiological, demographic, and digital infrastructure characteristics of Central Asia. This gap limits the ability of policymakers and healthcare providers to derive actionable insights for optimizing telemedicine adoption in the region.

This study proposes a predictive model based on artificial neural networks to estimate the number of telemedicine users in Central Asia. Using epidemiological data (e.g., disease prevalence, mortality rates), demographic indicators (e.g., population distribution, rural-urban divide), and digital infrastructure metrics (e.g., Internet access, electronic health record systems), the model aims to identify the key drivers of telemedicine adoption. The insights derived from this model have practical implications for healthcare management, policy planning, and digital health infrastructure investment decisions. By predicting the demand for telemedicine services, the model can support efforts to increase access to healthcare, improve the efficiency of remote medical services, and develop targeted strategies to promote telemedicine adoption across Central Asia.

2. MATERIALS AND METHODS

2.1. Data overview

The data used in the analysis is publicly available and can be accessed through public statistics portals, although access to some more specific data (e.g., internal ministry reports or recent data) may require permission or additional requests. The analysis period includes current data through 2024, allowing for an assessment of current trends and prospects for telemedicine adoption in the countries of the region, as well as taking into account changes in legislation, infrastructure, and healthcare delivery over the past decade.

1. Epidemiologic data: Assessing the burden on the health care system

Epidemiologic data includes information on the prevalence of common diseases and leading causes of mortality in the population. This category includes lung cancer cases, cardiovascular disease (CVD) cases, tuberculosis prevalence, all-cause mortality, CVD mortality, cancer mortality, diabetes mortality, and tuberculosis mortality. These indicators reflect the prevalence and mortality of major diseases that affect health needs. Epidemiological data can help identify which diseases drive the demand for telehealth services. Regions with a high prevalence of chronic diseases, such as CVD or diabetes, may have a higher demand for telehealth services. Therefore, telehealth development programs should focus on the prevention and management of these diseases.

Tab. 1. Epidemiological data for Central Asia from 2014 to 2024

Diseases	Country*	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Lung cancer (per 100,000 people)	KZ	32,1	33	33,8	34,4	35	35,5	36	35,7	35,2	35,1	35,2
	KR	17,5	18,1	18,4	18,8	19	19,5	19,8	19,9	18,8	19	18,2
	UZ	310	315	320	325	330	335	340	345	350	355	360
	TJ	13	13,5	14	14,3	14,6	15	15,5	16	16,2	16,5	15,5
	TM	8	8,2	8,4	8,5	8,7	8,9	9	9,1	9,2	9,3	10,2
Cardiovascular diseases (per 100,000 people)	KZ	280,5	282,1	284	285,3	287	290	295	298,1	301	305,2	310,3
	KR	210,5	212,3	214	217	220	225	230	235	240,1	245,2	250
	UZ	28,5	29	29,5	30,2	30,5	31	31,2	31,8	32	32,5	32,7
	TJ	250	255	260	265	270	275	280	285	290	295	300
	TM	300	305	310	315	320	325	330	335	340	345	350
Diabetes mellitus (per 100,000 people)	KZ	18,2	18,5	19	19,3	19,8	20,2	20,5	21	21,5	22	22,3
	KR	14,5	14,8	15,2	15,6	16	16,5	17	17,5	18	18,5	19
	TJ	12	12,2	12,5	12,8	13,1	13,5	14	14,3	14,7	15	15,3
	TM	18	18,3	18,6	18,8	19	19,5	20	20,4	20,6	20,8	20,3
Tuberculosis (per 100,000 people)	KZ	40,1	38,3	37,6	36,9	36,2	35,5	34,8	34	33,4	32,8	32,1
	KR	13	13,5	14,1	14,3	14,5	14,8	15	15,4	14,2	14,5	14,4
	UZ	18,3	18,5	19	19,4	19,6	20,1	20,4	20,8	21,2	21,5	22,1
	TJ	45	44	43	42	41	40	39	38	37	36	35,6
	TM	23	24	25	25,5	26	27	28	29	29,5	30	25,8

*KZ – Kazakhstan, KR – Kyrgyzstan, UZ – Uzbekistan, TJ – Tadjikistan, TM – Turkmenistan

Tab. 2. Basic statistical analysis for epidemiological data

Diseases	Country*	Min	Max	Mean	Std_Dev
Lung cancer (per 100,000 people)	KZ	280.5	310.3	292.59	10.00
	KR	210.5	250.0	227.19	13.84
	UZ	250.0	300.0	275.00	16.58
	TJ	300.0	350.0	325.00	16.58
	TM	28.5	32.7	30.81	1.41
Cardiovascular diseases (per 100,000 people)	KZ	18.2	22.3	20.21	1.39
	KR	14.5	19.0	16.60	1.53
	UZ	12.0	15.3	13.58	1.15
	TJ	18.0	20.8	19.48	0.99
	TM	32.1	36.0	34.64	1.21
Diabetes mellitus (per 100,000 people)	KZ	17.5	19.9	18.82	0.74
	KR	13.0	16.5	14.92	1.14
	TJ	8.0	10.2	8.86	0.61
	TM	310.0	360.0	335.00	16,58
Tuberculosis (per 100,000 people)	KZ	32.1	40.1	35.61	2.48
	KR	13.0	15.4	14.34	0.66
	UZ	35.6	45.0	40.05	3.23
	TJ	23.0	30.0	26.62	2.29
	TM	18.3	22.1	20.08	1.24

*KZ – Kazakhstan, KR – Kyrgyzstan, UZ – Uzbekistan, TJ – Tadjikistan, TM - Turkmenistan

Table 1 presents disease prevalence data from 2014 to 2024 for Kazakhstan, Kyrgyzstan, Uzbekistan, Tajikistan, and Turkmenistan. The data highlight significant trends, including a steady increase in lung cancer cases, with Uzbekistan reporting the highest prevalence. Cardiovascular disease has increased significantly in Turkmenistan and Kazakhstan, while diabetes cases have increased significantly in Kazakhstan and Kyrgyzstan. Tuberculosis rates have decreased in Kazakhstan and Tajikistan, but have remained stable or increased in other regions. Table 2 provides a statistical summary with a detailed description of the minimum, maximum, average and standard deviation of disease prevalence rates for each country. Uzbekistan has the highest average prevalence of lung cancer (335.00 per 100,000), while Turkmenistan has the highest rate of cardiovascular disease (34.64 per 100,000). Diabetes mellitus is most prevalent in TM (average: 335.00 per 100,000), reflecting the growing burden of chronic disease. Although tuberculosis incidence rates are declining in some countries, alarming trends are still evident in the United States (average: 40.05 per 100,000).

2. Demographic Data: Population structure and access to health care

Demographic data provides information on the structure and characteristics of the population. This category includes total population, gender distribution, age group distribution, and urban versus rural population. These factors influence the demand for and accessibility of healthcare services and provide insight into which populations are more likely to require telehealth services.

Tab. 3. Mortality rates data for Central Asia for 2014 to 2024

Mortality rates data	Country*	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Total mortality (per 1,000 people)	KZ	8.3	8.0	7.8	7.7	7.5	7.3	7.2	7.1	6.9	6.7	6.6
	KR	7.9	7.8	7.6	7.5	7.4	7.3	7.2	7.1	7.0	6.9	6.8
	UZ	6.9	6.8	6.7	6.6	6.5	6.4	6.3	6.2	6.1	6.0	5.9
	TJ	8.0	7.9	7.8	7.7	7.6	7.5	7.4	7.3	7.2	7.1	7.0
	TM	5.9	5.8	5.7	5.6	5.5	5.4	5.3	5.2	5.1	5.0	4.9
Mortality from cardiovascular diseases (per 100,000)	KZ	1850	1800	1780	1750	1700	1680	1650	1600	1580	1550	1520
	KR	1900	1850	1800	1750	1700	1650	1600	1550	1500	1480	1450
	UZ	1950	1900	1850	1800	1750	1700	1650	1600	1550	1500	1450
	TJ	2000	1950	1900	1850	1800	1750	1700	1650	1600	1550	1500
	TM	1800	1750	1700	1650	1600	1550	1500	1450	1400	1350	1300
Cancer mortality (per 100,000)	KZ	120	122	125	128	130	135	140	145	148	150	153
	KR	110	112	115	118	120	123	125	128	130	133	135
	UZ	115	118	120	122	125	128	130	133	135	137	140
	TJ	100	105	110	115	120	125	130	135	140	142	145
	TM	90	95	100	105	110	115	120	125	130	135	140
Deaths from diabetes (per 100,000)	KZ	8.5	9.0	9.2	9.5	10.0	10.3	10.5	11.0	11.2	11.5	12.0
	KR	9.0	9.2	9.5	9.7	10.0	10.3	10.5	11.0	11.2	11.5	12.0
	UZ	8.5	8.7	9.0	9.3	9.5	9.8	10.0	10.3	10.5	10.8	11.0
	TJ	8.5	8.7	9.0	9.3	9.5	9.8	10.0	10.3	10.5	10.8	11.0
	TM	7.0	7.2	7.5	7.8	8.0	8.2	8.5	8.8	9.0	9.3	9.5
Tuberculosis mortality (per 100,000)	KZ	18	17	16.5	16.0	15.8	15.5	15.0	14.8	14.5	14.0	13.8
	KR	28.0	34.0	33.5	32.5	31.8	31.0	30.5	30.0	29.5	28.8	28.0
	UZ	22.0	21.8	21.5	21.0	20.5	20.2	19.8	19.5	19.0	18.5	18.0
	TJ	45.0	44.5	44.0	43.5	43.0	42.5	42.0	41.5	40.0	40.5	40.0
	TM	23.0	22.5	22.0	21.8	21.5	21.0	20.8	20.5	20.2	19.8	19.5

*KZ – Kazakhstan, KR – Kyrgyzstan, UZ – Uzbekistan, TJ – Tadjikistan, TM - Turkmenistan

Tab. 4. Statistical analysis of demographic data

Mortality rates data	Country*	Min	Max	Mean	Std_Dev
Total mortality (per 1,000 people)	KZ	6.6	8.3	7.46	0.59
	KR	6.8	7.9	7.39	0.36
	UZ	5.9	6.9	6.35	0.32
	TJ	7.0	8.0	7.58	0.35
	TM	4.9	5.9	5.35	0.32
Mortality from cardiovascular diseases (per 100,000)	KZ	1520	1850	1689.09	111.52
	KR	1450	1900	1666.36	158.59
	UZ	1450	1950	1695.45	173.25
	TJ	1500	2000	1727.27	173.25
	TM	1300	1800	1540.91	173.25
Cancer mortality (per 100,000)	KZ	120	153	135.64	10.79
	KR	110	135	123.09	7.90
	UZ	115	140	127.36	8.09
	TJ	100	145	123.45	14.98
	TM	90	140	115.91	16.16
Deaths from diabetes (per 100,000)	KZ	8.5	12.0	10.29	1.19
	KR	9.0	12.0	10.38	1.08
	UZ	8.5	11.0	9.67	0.85
	TJ	8.5	11.0	9.67	0.85
	TM	7.0	9.5	8.15	0.76
Tuberculosis mortality (per 100,000)	KZ	13.8	18.0	15.71	1.37
	KR	28.0	34.0	30.87	2.08
	UZ	18.0	22.0	20.49	1.36
	TJ	40.0	45.0	42.31	1.78
	TM	19.5	23.0	21.32	1.14

*KZ – Kazakhstan, KR – Kyrgyzstan, UZ – Uzbekistan, TJ – Tadjikistan, TM - Turkmenistan

For example, remote monitoring and consultation services may be in demand in areas with a large elderly population, while telemedicine may provide rural residents with access to specialists. Therefore, analyzing demographic data can help tailor telehealth services to the needs of each population.

Table 3 shows mortality rates from 2014 to 2024 for Kazakhstan, Kyrgyzstan, Uzbekistan, Tajikistan, and Turkmenistan. The data show a decline in overall mortality, although Tajikistan remains at a high level. While mortality from cardiovascular disease has also decreased, deaths from cancer and diabetes are increasing. Turkmenistan has the lowest overall mortality rate. Table 4 provides a statistical summary of the minimum, maximum, average, and standard deviation of mortality rates for each country.

Tajikistan has high tuberculosis mortality and high all-cause mortality. Turkmenistan has high mortality from cardiovascular disease but low all-cause mortality. Kazakhstan has higher cancer mortality. Mortality from diabetes is increasing in all countries.

Tab. 5. Demographic data for Central Asia from 2014 to 2024

Demographic data	Country*	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Total population (million people)	KZ	17.2	17.5	15.7	18.0	18.2	18.4	18.6	18.8	19.0	19.2	19.4
	KR	5.8	5.9	6.0	6.1	6.2	6.3	6.4	6.5	6.6	6.7	6.8
	UZ	30.6	31.1	31.6	32.0	32.4	32.9	33.3	33.7	34.1	34.5	34.9
	TJ	8.3	8.5	8.7	8.9	9.1	9.3	9.5	9.7	9.9	10.1	10.3
	TM	5.3	5.4	5.5	5.6	5.7	5.8	5.9	6.0	6.1	6.2	6.3
Men (%)	KZ	48.0	48.1	48.2	48.3	48.4	48.5	48.6	48.7	48.8	48.9	49.0
	KR	49.3	49.2	49.1	49.0	48.9	48.8	48.7	48.6	48.5	48.4	48.3
	UZ	49.5	49.4	49.3	49.2	49.1	49.0	48.9	48.8	48.7	48.6	48.5
	TJ	49.3	19.2	49.1	49.0	48.8	48.7	48.6	48.5	48.4	48.3	48.2
	TM	49.7	49.6	49.5	49.4	49.3	49.2	49.1	49.0	48.9	48.8	48.7
Women (%)	KZ	52.0	51.9	51.8	51.7	51.6	51.5	51.4	51.3	51.2	51.1	51.0
	KR	50.7	50.8	50.9	51.0	51.1	51.2	51.3	51.4	51.5	51.6	51.7
	UZ	50.5	50.6	50.7	50.8	50.9	51.0	51.1	51.2	51.3	51.4	51.5
	TJ	50.7	50.8	50.9	51.1	51.2	51.3	51.4	51.5	51.6	51.7	51.8
	TM	50.3	50.4	50.5	50.6	50.7	50.8	50.9	51.0	51.1	51.2	51.3
0-14 years old (%)	KZ	23.0	22.8	22.5	22.3	22.0	21.8	21.5	21.2	21.0	20.8	20.5
	KR	31.4	30.8	30.0	29.5	29.0	28.5	28.0	27.5	27.0	26.5	26.0
	UZ	31.2	30.8	30.4	30.0	29.5	29.0	28.5	28.0	27.5	27.0	26.5
	TJ	39.5	38.9	38.3	37.7	37.1	37.5	36.0	35.4	34.8	34.2	33.7
	TM	38.9	38.5	38.1	37.6	37.2	36.8	36.4	36.0	35.6	35.2	34.8
15-64 years old (%)	KZ	67.5	67.3	67.0	66.8	66.5	66.2	65.9	65.7	65.6	65.3	65.0
	KR	61.2	61.5	61.9	62.1	62.3	62.5	62.7	62.9	63.1	63.3	63.5
	UZ	63.2	63.5	63.8	64.1	64.3	64.5	64.7	64.9	65.1	65.3	65.5
	TJ	56.2	56.7	57.1	57.5	57.9	58.3	58.7	59.0	59.3	59.7	60.0
	TM	57.1	57.3	27.5	57.8	58.0	58.2	58.4	58.6	58.8	59.0	59.2
65+ years old (%)	KZ	9.5	9.9	10.5	11.0	11.5	12.0	12.6	13.0	13.5	14.0	14.5
	KR	7.4	7.7	8.1	8.4	8.7	9.0	9.2	9.5	9.8	10.0	10.2
	UZ	5.6	5.7	5.8	5.9	6.0	6.1	6.2	6.3	6.4	6.5	6.6
	TJ	4.3	4.4	4.6	4.8	5.0	5.2	5.3	5.6	5.8	6.0	6.2
	TM	4.0	4.2	4.4	4.6	4.8	5.0	5.2	5.4	5.6	5.8	6.0
Urban population (%)	KZ	57.0	58.0	59.0	60.0	61.0	62.0	63.0	64.0	65.0	66.0	67.0
	KR	34.0	34.5	35.0	35.5	36.0	36.5	37.0	37.5	38.0	38.5	39.0
	UZ	36.5	37.0	37.5	38.0	38.5	39.0	39.5	40.0	40.5	41.0	41.5
	TJ	27.5	28.0	28.5	29.0	29.5	30.0	30.5	31.0	31.5	32.0	32.5
	TM	44.0	44.5	45.0	45.5	46.0	46.5	47.0	47.5	48.0	48.5	49.0
Rural population (%)	KZ	43.0	42.0	41.0	40.0	39.0	38.0	37.0	36.0	35.0	34.0	33.0
	KR	66.0	65.5	65.0	64.5	64.0	63.5	63.0	62.5	62.0	61.5	61.0
	UZ	63.5	63.0	62.5	62.0	61.5	61.0	60.5	60.0	59.5	59.0	58.5
	TJ	72.5	72.0	71.5	71.0	70.5	70.0	69.5	69.0	68.5	68.0	67.5
	TM	56.0	55.5	55.0	54.5	54.0	53.5	53.0	52.5	52.0	51.5	51.0
Poverty rate (%)	KZ	2.9	2.7	2.6	2.5	2.4	2.1	2.0	2.1	2.0	1.9	1.9
	KR	36.0	34.5	32.0	30.5	28.9	27.0	25.5	24.0	22.5	21.0	21.0
	UZ	14.3	13.8	13.5	13.0	12.5	12.0	11.5	11.0	10.5	10.0	10.0
	TJ	32.0	31.5	31.0	30.5	30.0	29.5	29.0	28.5	28.0	27.5	27.0
	TM	30.5	30.0	29.5	29.0	28.5	28.0	27.5	27.0	26.5	26.0	25.5

*KZ – Kazakhstan, KR – Kyrgyzstan, UZ – Uzbekistan, TJ – Tadjikistan, TM - Turkmenistan

Tab. 6. Basic statistical analysis for demographic indicators

Demographic data	Country*	Min	Max	Mean	Std_Dev
Total population (million people)	KZ	15.7	19.4	18.25	1.25
	KR	5.8	6.8	6.35	0.32
	UZ	30.6	34.9	32.89	1.45
	TJ	8.3	10.3	9.26	0.69
	TM	5.3	6.3	5.78	0.32
Men (%)	KZ	48.0	49.0	48.55	0.32
	KR	48.3	49.3	48.83	0.36
	UZ	48.5	49.5	49.00	0.32
	TJ	48.2	49.3	48.75	0.34
	TM	48.7	49.7	49.20	0.32
Women (%)	KZ	51.0	52.0	51.45	0.32
	KR	50.7	51.7	51.17	0.36
	UZ	50.5	51.5	51.00	0.32
	TJ	50.7	51.8	51.45	0.36
	TM	50.3	51.3	50.80	0.32
0-14 years old (%)	KZ	20.5	23.0	21.84	0.86
	KR	26.0	31.4	28.64	1.78
	UZ	26.5	31.2	28.85	1.61
	TJ	33.7	39.5	36.47	1.94
	TM	34.8	38.9	37.16	1.27
15-64 years old (%)	KZ	65.0	67.5	66.42	0.86
	KR	61.2	63.5	62.54	0.78
	UZ	63.2	65.5	64.37	0.78
	TJ	56.2	60.0	58.24	1.33
	TM	55.2	59.2	57.89	1.33
65+ years old (%)	KZ	9.5	14.5	11.74	1.69
	KR	7.4	10.2	8.82	0.88
	UZ	5.6	6.6	6.12	0.32
	TJ	4.3	6.2	5.29	0.65
	TM	4.0	6.0	5.06	0.65
Urban population (%)	KZ	57.0	67.0	62.36	3.60
	KR	34.0	39.0	36.64	1.78
	UZ	36.5	41.5	39.14	1.78
	TJ	27.5	32.5	29.82	1.78
	TM	44.0	49.0	46.73	1.78
Rural population (%)	KZ	33.0	43.0	37.64	3.60
	KR	61.0	66.0	63.36	1.78
	UZ	58.5	63.5	60.86	1.78
	TJ	67.5	72.5	70.18	1.78
	TM	51.0	56.0	53.27	1.78
Poverty rate (%)	KZ	1.9	2.9	2.30	0.37
	KR	21.0	36.0	28.22	5.01
	UZ	10.0	14.3	12.33	1.43
	TJ	27.0	32.0	29.77	1.61
	TM	25.5	30.5	28.18	1.61

*KZ – Kazakhstan, KR – Kyrgyzstan, UZ – Uzbekistan, TJ – Tadjikistan, TM - Turkmenistan

Table 5 shows demographic data for Kazakhstan, Kyrgyzstan, Uzbekistan, Tajikistan, and Turkmenistan from 2014 to 2024. According to the data, the population is growing in all countries. There is no significant change in the ratio of men to women. The proportion of children aged 0-14 is decreasing, while the proportion of people over 65 is increasing. The urban population is growing, while the rural population is declining. Poverty rates are on the decline in all countries. Table 6 provides a statistical summary of the demographic indicators of the Central Asian countries. Kazakhstan has an average population size, but is characterized by a predominance of urban residents and low poverty. Tajikistan has a high proportion of children and a large rural population. Uzbekistan is one of the most densely populated countries. Kyrgyzstan has a variable poverty rate. Turkmenistan has a significant variation in the share of the working age population.

3. Digital infrastructure: Technology capabilities for telehealth implementation

Digital infrastructure is a key factor that directly affects telehealth adoption. This category includes Internet access, electronic health record (EHR) infrastructure, and telehealth users. Widespread Internet access and its speed ensure access to telemedicine services. The presence of an EHR system enables the secure storage and exchange of medical data, which increases the accuracy of diagnoses and the effectiveness of treatment. The number of telemedicine users indicates the popularity of this technology among the population. Therefore, improving the digital infrastructure is an essential condition for the effective implementation of telemedicine.

The EHR variable does not indicate the level of access of the population to such devices, i.e. electronic health records. This variable typically refers to the extent to which health care facilities or providers use the EHR system or the availability of such systems within the health care infrastructure. In other words, this measure does not refer to the general population, but rather provides information about the level of use of electronic health records within the healthcare sector.

Tab.7. Data on digital infrastructure in Central Asia for 2014 to 2024

Data on digital infrastructure	Country*	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Internet access (%)	KZ	72.0	74.5	77.0	80.0	83.0	86.0	89.0	92.0	94.0	95.0	97
	KR	64.5	66.0	68.5	71.0	73.0	75.5	78.5	80.0	82.0	84.0	85.5
	UZ	53.0	56.0	60.0	63.0	66.0	69.0	72.5	75.0	78.0	80.5	83.0
	TJ	22.0	25.0	28.0	32.0	35.0	38.0	42.0	46.0	50.0	53.0	55.0
	TM	27.0	30.0	33.0	36.0	40.0	43.0	47.0	50.0	53.0	56.0	58.0
Number of telemedicine users (million)	KZ	0.1	0.2	0.3	0.4	0.5	0.8	1.2	1.6	2.0	2.5	3.0
	KR	0.05	0.1	0.2	0.3	0.4	0.6	0.9	1.1	1.3	1.6	2.0
	UZ	0.03	0.05	0.07	0.1	0.15	0.25	0.4	0.55	0.75	1.0	1.5
	TJ	0.02	0.03	0.05	0.07	0.1	0.2	0.3	0.5	0.7	1.0	1.2
	TM	0.01	0.02	0.03	0.05	0.08	0.1	0.2	0.3	0.4	0.6	0.8
EHR (Electronic Medical Records) Infrastructure (%)	KZ	15	18	22	27	35	45	55	65	75	85	90
	KR	10	12	15	18	22	30	35	42	50	60	65
	UZ	5	7	10	15	20	30	40	50	60	70	75
	TJ	3	5	7	10	15	20	30	40	50	60	65
	TM	5	6	8	10	12	15	18	22	25	30	35

*KZ – Kazakhstan, KR – Kyrgyzstan, UZ – Uzbekistan, TJ – Tadjikistan, TM - Turkmenistan

Tab.8. Basic statistical analysis for digital infrastructure

Data on digital infrastructure	Country*	Min	Max	Mean	Std_Dev
Internet access (%)	KZ	72.0	97.0	85.9	8.91
	KR	64.5	85.5	74.7	7.21
	UZ	53.0	83.0	68.7	9.87
	TJ	22.0	55.0	40.5	11.81
	TM	27.0	58.0	42.0	11.44
Number of telemedicine users (million)	KZ	0.1	3.0	1.13	0.94
	KR	0.05	2.0	0.74	0.62
	UZ	0.03	1.5	0.43	0.44
	TJ	0.02	1.2	0.32	0.37
	TM	0.01	0.8	0.24	0.24
EHR (Electronic Medical Records) Infrastructure (%)	KZ	15	90	51.9	26.46
	KR	10	65	31.6	18.48
	UZ	5	75	35.6	23.06
	TJ	3	65	29.7	22.15
	TM	5	35	17.3	9.55

*KZ – Kazakhstan, KR – Kyrgyzstan, UZ – Uzbekistan, TJ – Tadjikistan, TM - Turkmenistan

Table 7 shows digital infrastructure development indicators for Kazakhstan, Kyrgyzstan, Uzbekistan, Tajikistan, and Turkmenistan between 2014 and 2024. The data show increased internet access, a growing number of telemedicine users, and improvements in electronic health record infrastructure. Kazakhstan and Kyrgyzstan are leaders in the development of digital medicine. However, Tajikistan and Turkmenistan show slower development of digital medicine, while Uzbekistan's development rate is at a moderate level. Table 8 provides a statistical summary detailing the minimum, maximum, mean, and standard deviation of digital infrastructure development for each country. Kazakhstan has the highest mean for Internet access and EHR infrastructure, indicating advanced digital health systems. The use of telemedicine is also highest in Kazakhstan. While all countries show growth in these areas, Tajikistan and Turkmenistan have lower averages across all indicators, suggesting a need for further investment in digital infrastructure.

2.2. Statistical analysis and selection of input variables for the model

The statistical analysis was conducted to ensure the appropriate selection of variables that influence the adoption of telemedicine. First, descriptive statistics were generated to assess the distribution, central tendency, and variation of each variable. The data were examined for outliers and inconsistencies to confirm their suitability for predictive modeling. Mean, standard deviation, minimum, and maximum values were calculated to understand the range of variation in health and technology factors across Central Asian countries.

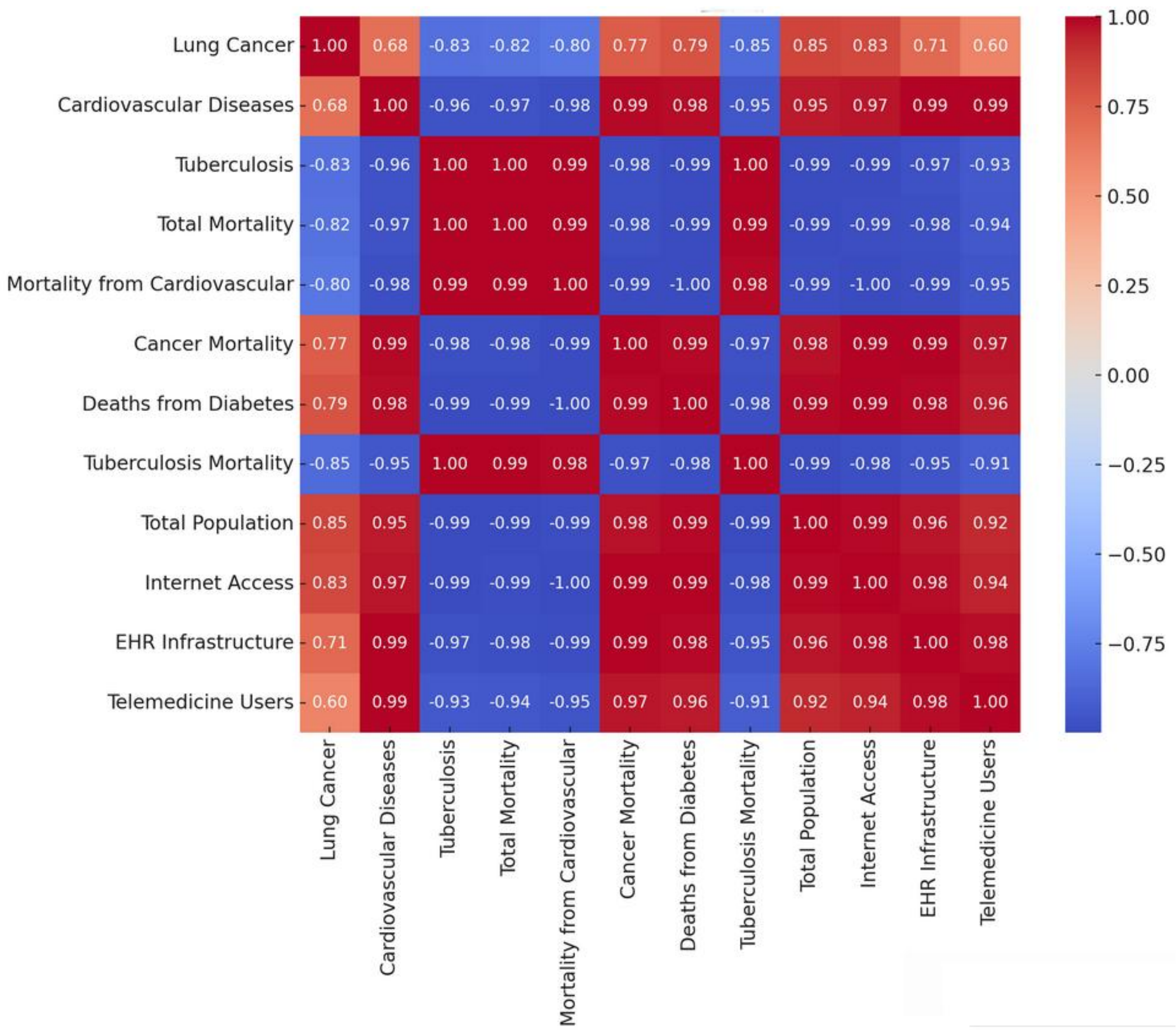


Fig. 1. Correlation matrix for analyzed variables

A correlation matrix was calculated to determine the relationships between telemedicine adoption and other variables. The highest correlations were observed for cardiovascular disease (r = 0.99), EHR infrastructure (r = 0.98), cancer mortality (r = 0.96), and diabetes mortality (r = 0.95). These variables were found to be the most reliable predictors of telemedicine adoption and were selected as input characteristics for the model. The number of telemedicine users was set as the target output variable for prediction. These selected characteristics not only show statistical significance, but also align with logical healthcare trends, highlighting the role of chronic disease and digital infrastructure in driving telehealth growth.

2.3. Modeling methodology

Artificial neural networks (ANNs) were used to model and predict the number of telemedicine users based on key epidemiological and digital health infrastructure factors. The network was trained using Matlab R2024b (The MathWorks, Inc., Natick, Massachusetts, United States). A shallow neural network with a single hidden layer was used for simplicity and efficiency. The input layer consisted of four neurons corresponding to the most reliable predictors of telemedicine adoption: cardiovascular disease prevalence, EHR infrastructure level, cancer mortality rate, and diabetes mortality rate. The output layer contained a single neuron representing the predicted number of telehealth users.

The network was trained using the Levenberg-Marquardt (LM) algorithm, with additional evaluation using the Scaled Conjugate Gradient (SCG) and Bayesian Regularization (BR) algorithms. The number of neurons in the hidden layer (ranging from 2 to 15) was chosen experimentally. The maximum number of training epochs was set to 1000. The data set was divided into 75% training data and 25% validation data. Due to the limited size of the data set, a separate test group was not included.

When selecting the network training parameters, the standard weight initialization method was used to ensure stable initial conditions for the training process. Proper weight initialization allows the model to effectively start the optimization process, which is especially important when dealing with a limited data set.

In the hidden layer, a sigmoidal activation function was used, which is widely used in modeling nonlinear relationships between input and output variables. This function allows the model to capture complex patterns in the input data, which is critical for achieving high prediction accuracy. To evaluate the model performance, the Mean Squared Error (MSE) cost function was used, which is a common metric in regression problems.

To avoid overfitting, an early stopping mechanism was implemented. The early stopping criterion was set to 6 epochs, meaning that the training process would be stopped if no improvement in validation performance was observed for six consecutive epochs. This approach ensures that the model does not overlearn the training data while maintaining its generalization ability.

Several key performance indicators were analyzed to evaluate the accuracy and reliability of the model:

1. Correlation Coefficient (R)

The correlation coefficient measures the strength of the linear relationship between actual and predicted values and is calculated as:

$$R(y', y^*) = \frac{cov(y', y^*)}{\sigma_{y'}\sigma_{y^*}} \qquad R\epsilon < 0{,}1 > \tag{1}$$

where: y' represents the actual number of telemedicine users,
y^* represents the predicted number of telemedicine users,
$\sigma_{y'}$ is the standard deviation of the actual values,
σ_{y^*} is the standard deviation of the predicted values,
$cov(y', y^*)$ denotes the covariance between actual and predicted values.

2. Mean Squared Error (MSE)

MSE quantifies the mean squared difference between predicted and actual values, given by

$$\mathrm{MSE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}}(y_i{}^* - y_i{}')^2 \tag{2}$$

where: n is the total number of observations.

3. Root Mean Squared Error (RMSE)

The RMSE is the square root of the MSE, so it can be interpreted in the same unit as the original data:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}}(y_i{}^* - y_i{}')^2} \tag{3}$$

4. Relative Improvement Error (RIE):

RIE measures the relative error between predicted and actual values:

$$RIE = \frac{\|y' - y^*\|}{\|y'\|} \tag{4}$$

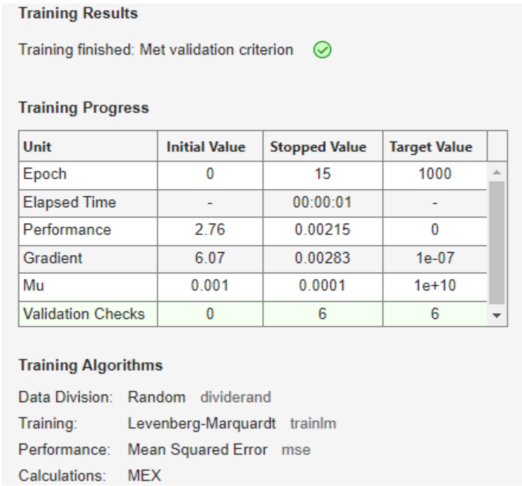
5. Mean Absolute Error (MAE):

MAE calculates the average absolute differences between predicted and actual values:

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}|y_i^* - y_i'| \qquad (5)$$

3. RESULTS

The best results for modeling the number of telemedicine users were obtained using a neural network with 8 neurons in the hidden layer, trained with the Levenberg-Marquardt (LM) algorithm. The training structure and its parameters are shown in Figure 2. The training process successfully met the validation criterion, indicating that the model maintained a balance between learning from the data and avoiding overfitting. Training was set to a maximum of 1000 epochs; however, the process was automatically stopped after 15 epochs due to the early stopping mechanism set at 6 validation checks. That is, if the validation performance did not improve for six consecutive epochs, training was stopped to avoid overfitting.


Training Results

Training finished: Met validation criterion

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	15	1000
Elapsed Time	-	00:00:01	-
Performance	2.76	0.00215	0
Gradient	6.07	0.00283	1e-07
Mu	0.001	0.0001	1e+10
Validation Checks	0	6	6

Training Algorithms

Data Division: Random dividerand

Training: Levenberg-Marquardt trainlm

Performance: Mean Squared Error mse

Calculations: MEX

Fig. 2. Neural network training parameters for modeling the number of telemedicine users

Training performance, as assessed by the Mean Squared Error (MSE) function, showed a significant reduction in error during the training process (Figure 3). The initial MSE value was 2.76, which decreased to 0.00215 at the stop epoch. The validation dataset achieved its best performance at epoch 9, where the validation MSE reached 0.020063. This point is marked in the performance graph, confirming that the network reached its optimal prediction capability before training stopped at epoch 15. The gradient, which represents the rate of error reduction, started at 6.07 and gradually decreased to 0.00283 at epoch 15, indicating stable convergence of the model (Figure 4). At the same time, the adaptive learning parameter (Mu), which controls the balance of weight updates, dynamically adjusted and stabilized at 0.0001, preventing overshooting during training.

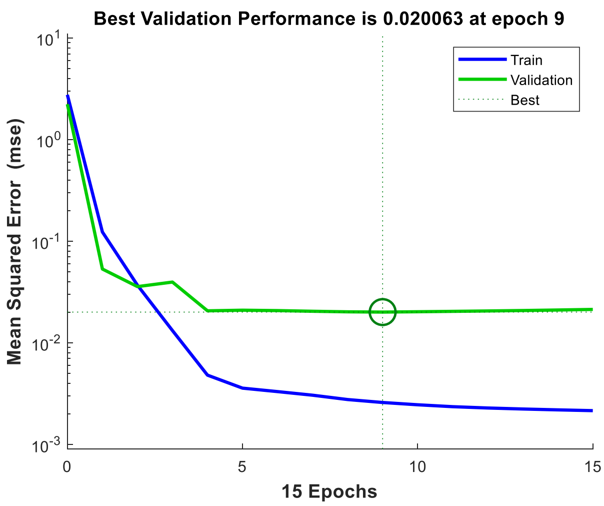


Fig. 3. Best validation performance for modeling the number of telemedicine users

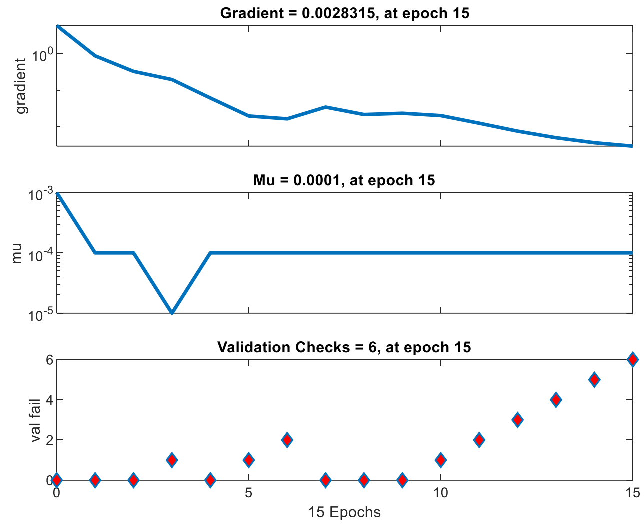


Fig. 4. Gradient, mu, and validation checks during neural network training

The error histogram analysis (Figure 5) showed that the majority of the prediction errors were concentrated around zero, further supporting the effectiveness of the network in approximating the target values. Most of the errors were small, with only a few outliers, indicating that the network generalized well over both the training and validation data sets.

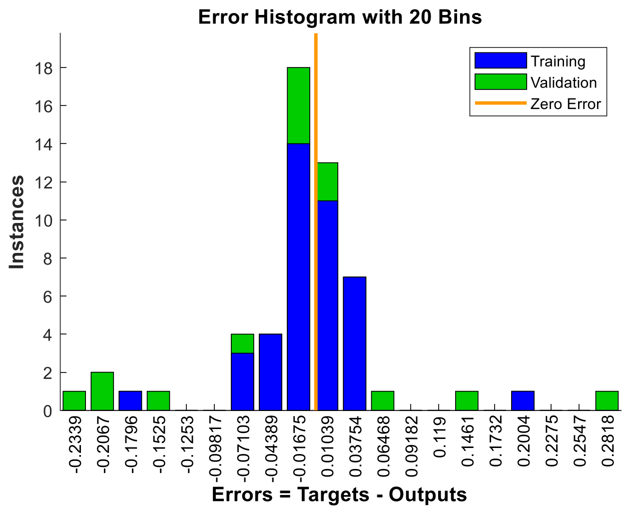


Fig. 5. Error histogram for modeling the number of telemedicine users

The correlation analysis between the predicted and actual values (Figure 6) showed a strong linear relationship across all data sets. The correlation coefficient for the training set was R = 0.99722, while it was slightly lower for the validation set at R = 0.9784. The overall correlation coefficient for the combined data set was R = 0.99245, confirming a near perfect fit between predictions and actuals. This strong correlation indicates that the selected predictors - cardiovascular disease prevalence, EHR infrastructure level, cancer mortality rate, and diabetes mortality rate - were highly effective in predicting telehealth adoption.

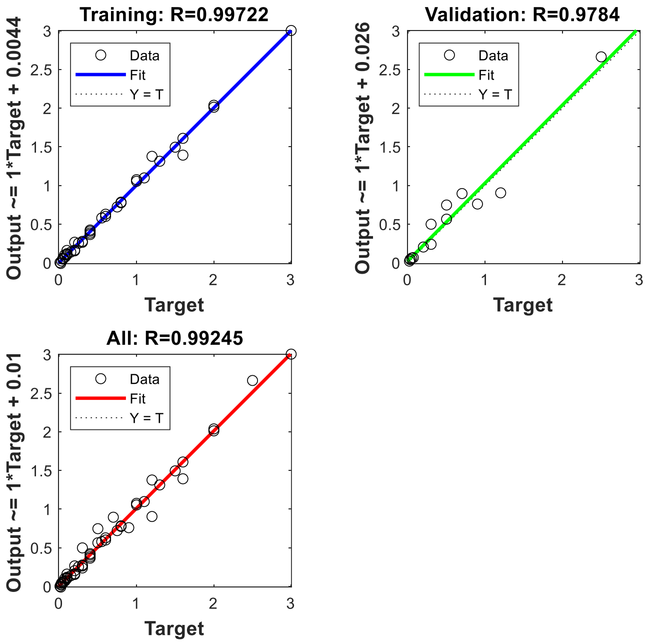


Fig. 6. The correlation analysis for modeling the number of telemedicine users

The final model evaluation metrics further confirmed the reliability of the model. The Mean Squared Error (MSE) was 0.007 and the Root Mean Squared Error (RMSE) was 0.0839, both indicating minimal prediction error. In addition, the Relative Improvement Error (RIE) was 0.0934 and the Mean Absolute Error (MAE) was 0.0479. These values reflect a well-optimized model capable of accurately predicting the number of telemedicine users.

These modeling results are consistent with findings in the broader literature emphasizing the integration of artificial intelligence in digital health. Tsvetanov (2024) highlights the transformative role of AI in enabling real-time monitoring and early intervention, particularly for chronic patients with limited access to in-person care. Regin and Rajest (2024) further demonstrate that data-driven intelligence, such as predictive models and deep neural networks, can significantly improve the efficiency of remote patient monitoring systems. Their work supports the use of AI to personalize treatment and predict health outcomes, which is consistent with the accurate predictive capabilities of our model. In addition, Velayati et al. (20-22) highlight the role of AI technologies in shaping telemedicine business models and demonstrate how AI can improve healthcare accessibility by predicting patient behavior and treatment seeking intentions. Taken together, these studies validate the approach and predictors used in our ANN-based model and reinforce its practical relevance for advancing telemedicine adoption in Central Asia.

4. CONCLUSIONS

This research focused on identifying the key factors that directly influence the number of telemedicine users in Central Asia. Using applied computer science tools and methods, we comprehensively analyzed critical aspects of the region, including the epidemiological situation, demographic characteristics of the population, and the level of digital infrastructure development.

The presented artificial neural network model, designed to predict the number of telemedicine users, provides a robust approach to assess the impact of key health and digital infrastructure indicators on telemedicine adoption. The model's high accuracy, demonstrated by strong correlation coefficients (R = 0.99245 for the entire dataset) and low prediction error (MSE = 0.0070, RMSE = 0.0839, MAE = 0.0479), confirms its reliability in predicting telemedicine adoption trends. The model effectively integrates epidemiological data - cardiovascular disease prevalence, EHR infrastructure level, cancer mortality rate, and diabetes mortality rate - with digital health indicators, providing a data-driven method for optimizing telemedicine expansion strategies.

The ability to accurately predict telemedicine adoption has broad practical implications. In health technology and biomedical applications, the model can support the planning and optimization of telehealth services, ensuring efficient allocation of medical resources and improving patient access to telehealth solutions. The results are particularly relevant to the development of digital health infrastructure, where policymakers and healthcare institutions can use predictive insights to guide investments in telehealth technologies and streamline decision-making processes.

In addition, this predictive approach can be integrated into industrial and automation systems, particularly in the context of smart healthcare technologies and automated diagnostics. By leveraging machine learning and neural networks, the model aligns with current trends in data-driven decision making, digital transformation, and AI-based medical systems, which are increasingly becoming essential components of modern healthcare management. The predictive framework can also be extended beyond healthcare applications, serving as a foundation for modeling other complex systems based on multivariable nonlinear relationships and digital infrastructure growth analysis.

The research presented highlights the role of machine learning, computational simulation, and data analytics in solving practical challenges related to healthcare and technological development. The ability to adapt this model to different domains underscores its relevance to areas requiring predictive analytics, system optimization, and intelligent automation. Future work may involve refining the model by integrating additional factors such as socioeconomic variables, regional healthcare accessibility, and technological advances, further strengthening its applicability in engineering, economics, and digital systems management.

Conflicts of Interest

The authors declare no conflict of interest.

REFERENCES

Bashshur, R., Doarn, C. R., Frenk, J. M., Kvedar, J. C., & Woolliscroft, J. O. (2020). Telemedicine and the COVID-19 pandemic, lessons for the future. *Telemedicine and e-Health*, *26*(5), 571–573. https://doi.org/10.1089/tmj.2020.29040.rb

Beam, A. L., & Kohane, I. S. (2018). Big data and machine learning in health care. *JAMA*, *319*(13), 1317–1318. https://doi.org/10.1001/jama.2017.18391

Cheng, T. C., & Yip, W. (2024). Policies, progress, and prospects for internet telemedicine in China. *Health systems and reform*, *10*(2), 2389570. https://doi.org/10.1080/23288604.2024.2389570

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology*, *2*(4), 230–243. https://doi.org/10.1136/svn-2017-000101

Katsaliaki, K. (2024). Factors influencing use of eHealth services during and after the COVID-19 pandemic. *Health Services Management Research*, *38*(2), 97-106. https://doi.org/10.1177/09514848241275777

Kruse, C. S., Karem, P., Shifflett, K., Vegi, L., Ravi, K., & Brooks, M. (2016). Evaluating barriers to adopting telemedicine worldwide: A systematic review. *Journal of Telemedicine and Telecare*, *24*(1), 4-12. https://doi.org/10.1177/1357633X16674087

Kruse, C. S., Krowski, N., Rodriguez, B., Tran, L., Vela, J., & Brooks, M. (2017). Telehealth and patient satisfaction: a systematic review and narrative analysis. *BMJ Open*, *7*(8), e016242. https://doi.org/10.1136/bmjopen-2017-016242

Kuo, T. T., Kim, H. E., & Ohno-Machado, L. (2017). Blockchain distributed ledger technologies for biomedical and health care applications. *Journal of the American Medical Informatics Association*, *24*(6), 1211–1220. https://doi.org/10.1093/jamia/ocx068

Makhlouf, Z., Laimeche, L., Meraoumia, A., & Haouam, M. Y. (2024). Enhancing medical data security in e-health systems using biometric-based watermarking. *Applied Computer Science*, *20*(1), 28–55. https://doi.org/10.35784/ACS-2024-03

Miotto, R., Li, L., Kidd, B. A., & Dudley, J. T. (2017). Deep patient: An unsupervised representation to predict the future of patients from the electronic health records. *Scientific Reports*, *6*, 26094. https://doi.org/10.1038/srep26094

Rajkomar, A., Oren, E., Chen, K., Dai, A. M., Hajaj, N., Hardt, M., Liu, P. J., Liu, X., Marcus, J., Sun, M., Sundberg, P., Yee, H., Zhang, K., Zhang, Y., Flores, G., Duggan, G. E., Irvine, J., Le, Q., Litsch, K., … Dean, J. (2018). Scalable and accurate deep learning with electronic health records. *Npj Digital Medicine*, *1*(1), 18. https://doi.org/10.1038/s41746-018-0029-1

Razzak, M. I., Imran, M., & Xu, G. (2019). Big data analytics for preventive medicine. *Neural Computing and Applications*, *32*(9), 4417–4451. https://doi.org/10.1007/s00521-019-04095-y

Regin, R., & Rajest, S. S. (2024). Leveraging data-driven intelligence for remote patient monitoring in digital health. *Central Asian Journal of Medical and Natural Science*, *5*(4), 798–808.

Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine*, *25*, 44–56. https://doi.org/10.1038/s41591-018-0300-7

Tsvetanov, F. (2024). Integrating AI technologies into remote monitoring patient systems. *Engineering Proceedings*, *70*(1), 54. https://doi.org/10.3390/engproc2024070054

Velayati, F., Ayatollahi, H., Hemmat, M., Dehghan, R. (2022). Telehealth business models and their components: Systematic review. *Journal of Medical Internet Research*, *24*(3), e33128. https://doi.org/10.2196/33128

Younis, M. C. (2024). Prediction of patient's willingness for treatment of mental illness using machine learning approaches. *Applied Computer Science*, *20*(2), 175–193. https://doi.org/10.35784/ACS-2024-23