Artificial Intelligence & Robotics Development Journal
Volume 5, Issue 3, pp 374-282, July 2025, https://doi.org/10.52098/airdj.20255347
ISSN: 2788-9696 Received: 14/4/2025 Revised: 22/4/2025 Accepted: 10/5/2025

Kazakhstan in the Global Economy: Rank, Growth, and Digital Adaptation from AI and Data Science Lens

Abu Shawer Omar Ahmad[1], Eimad Abusham[2], Kurmangali Aimen Kuanyshbaikyzy[1] & Saad Twaissi[3]
[1]Sorbonne-Kazakhstan Institute, Abai Kazakh National Pedagogical University: Almaty, Kazakhstan,
[2]Faculty of Computing & information Technology, Sohar University, Oman.
[3]Department of Tourism and Heritage studies, United Arab Emirates University, Al Ain, United Arab Emirates
* Corresponding author: Eimad Abusham[2], eabusham@su.edu.om.

Abstract

This study focuses on Kazakhstan's place in the global digital economy and offers a machine learning-based framework for evaluating preparedness for digital adaptation. To categories countries into three maturity groups—Digital Leaders, Transition Economies, and Digital Late Adopters. This study used principal component analysis (PCA) and K-Means clustering on a synthesized dataset of digital transformation proxies, which included mobile penetration, broadband access, e-government development, and innovation scores. Kazakhstan was regularly classified as a Transition Economy, suggesting moderate advancement in policy innovation and digital infrastructure. The results of this study are encouraging, with a 69% accurate Decision Tree classifier with high precision in identifying Digital Leaders, which was developed to predict readiness class with GDP. However, its susceptibility to distinguishing middle- and lower-tier economies implies the sophistication of digital transformation beyond economic stature. These results offer a data-driven path for moving Kazakhstan closer to digital maturity through focused investments, structural reforms, and insightful information on Kazakhstan's strategic location.

Keywords: College Digital Transformation, Principal Component Analysis (PCA), Kazakhstan, Machine Learning,

E-Government, Decision Tree Classification

1. Introduction

In the digital age, a country's capacity to adjust to and incorporate digital technology into its social, political, and economic systems has emerged as a crucial factor in determining its long-term competitiveness and success. A nation's ability to use information and communication technologies (ICTs) to promote innovation, increase the effectiveness of governance, and improve service delivery to both citizens and companies is reflected in its preparedness for digital adaptation (Moussa et al., 2025). Countries that lag behind in digital infrastructure, e-government, and innovation run the danger of experiencing structural stagnation and limited global integration as global economies grow more data-driven and technologically dependent.

Through programs like "Digital Kazakhstan," Kazakhstan, a Central Asian nation with abundant natural resources and a strategic location, has recognized the significance of digital transformation. These initiatives seek to strengthen intersectoral connectedness, modernize the nation's economy, and boost public administration (Bissaliyev et al., 2025). However, despite these efforts, Kazakhstan’s current position in the global digital ecosystem remains challenging and requires continued reform. The multifaceted nature of digital maturity, which includes technological infrastructure, digital literacy, institutional readiness, and innovation potential, is not well captured by standard macroeconomic statistics like GDP, despite the fact that they offer insights into economic production.

This paper suggests a machine learning-based approach (Yousif & Yousif, 2024) to evaluate and compare Kazakhstan's level of digital readiness to that of its international counterparts to close this gap. In particular, we use K-Means clustering to divide countries into three different digital maturity groups: Digital Leaders, Transition Economies, and Digital Late Adopters. This is implemented using principal component analysis (PCA) to reduce the dimensionality of key digital indicators, such as mobile penetration, broadband access, e-government index, and innovation score (Kazem et al., 20220). Although Kazakhstan's steady placement in the Transition Economies category shows quantifiable progress, it also highlights structural issues that, if ignored, could impede its digital development.

The degree to which GDP, as a stand-alone economic variable, can predict a nation's digital maturity group is investigated using a decision tree classifier in addition to unsupervised learning. The approach performs well in identifying Digital Leaders, but it has trouble distinguishing between Transition Economies and Late Adopters, highlighting the shortcomings of using economic size alone to gauge a nation's level of digital preparedness.

Both methodological and practical contributions are provided by this work (). In terms of methodology, it presents a data-driven, scalable, and interpretable framework for evaluating digital readiness that is transferable to various national contexts. In practice, the results offer useful information that policymakers, especially in Kazakhstan, can use to direct strategic investments in digital governance, broadband infrastructure, and innovation.

This study promotes the establishment of evidence-based digital strategies that are in line with both worldwide best practices and national development goals by identifying significant differentiators and evaluating Kazakhstan's standing globally.

2. Literature Review

By facilitating automation, predictive analytics, and data-driven decision-making, machine learning (ML) and artificial intelligence (AI) are revolutionizing how countries interact with the global economy (Alkishri et al., 2023). By maximizing resource allocation, improving service delivery, and forecasting market trends using sophisticated computational methodologies, AI and ML have the potential to propel digital adaption and economic progress in Kazakhstan. Applications in industries including identity verification, healthcare, and finance are already demonstrating AI's usefulness (Abusham & Zaabi, 2021; Al-Shibli & Abusham, 2017; Abusham & Bashier, 2013). Additionally, the synergy between data science and economic modeling is demonstrated by the integration of sentiment analysis and financial forecasts using soft computing (Saini, Zia, & Abusham, 2019). With artificial intelligence (AI) and data science playing a key role in promoting national growth, innovation, and labor market adaption, Kazakhstan's digital transformation is rapidly influencing its changing place in the global economy. Governments and businesses can now react to changes in the economy more skillfully because to the use of AI-based forecasting models and economic predictors (Ramírez et al., 2020). The nation's capacity to use data science for policymaking is demonstrated by the use of forecasting methods like ARIMA models to important national variables like migration (Tolesh & Biloshchytska, 2024). Furthermore, new insights into worker mobility and regional dynamics throughout Central Asia are being offered by AI-driven labor economics (Mansurov et al., 2022).

Numerous studies have examined the relationship between macroeconomic growth and the performance of the digital economy, confirming the close connection between economic development and digital innovation.

Economic diversification, digital adaptability, and creative solutions are becoming more and more important in Kazakhstan's participation in the global economy. Due to its long-standing reliance on natural resources, especially oil, the nation is susceptible to changes in world pricing. Diversification is urgently needed to reduce these vulnerabilities, according to recent studies. In their discussion of possible GDP trajectories under various global energy transition scenarios, for instance, Alpysbaeva et al. (2022) stress the need for Kazakhstan to modify its economic policies in order to stay competitive.

Small and medium-sized businesses (SMEs) play a critical role in Kazakhstan's economy's innovation. According to Shakenova (2018), SMEs play a crucial role in innovative activities for long-term, sustained development because they greatly enhance economic resilience and growth, urban innovations are also essential for raising living standards and promoting economic growth through the creation of smart cities (Shakenova A., 2018).

To raise Kazakhstan's economic status internationally, digital adaption is essential. Smart solutions and digital technology integration can boost productivity and creativity in a number of industries. According to Uteubayev and Petrova (2017), education and skill development are essential for using digital tools efficiently, underscoring the need of nurturing human potential in Kazakhstan's innovation economy (Uteubayev et al., 2018).

3. Methodology

In order to assess Kazakhstan's preparedness for digital adaption in comparison to its international peers, this study uses a machine learning-based methodology. To determine digital maturity groups and evaluate the predictive power of macroeconomic factors, especially GDP, on the classification of digital progress, the method combines supervised and unsupervised learning approaches (Yousif, J. & Yousif, M., 2023). A worldwide economic database comprising historical GDP data from 1960 to 2020 served as the basis for the analysis dataset, to which proxy indicators for digital adaption were included. In the lack of a single dataset on digital preparedness, these indicators—which comprised simulated values for mobile penetration, broadband access, e-government development index, and innovation score—acted as stand-ins for real digital performance measurements. These characteristics were chosen because they frequently show up in frameworks for the digital economy that are issued by organizations like the World Economic

Forum, OECD, and ITU. To guarantee equal weight during dimensionality reduction and clustering, z-score normalization was used to standardize all numerical variables.

3.1. Data Preparation and Feature Engineering

A worldwide economic database comprising historical GDP data from 1960 to 2020 served as the basis for the analysis dataset, to which proxy indicators for digital adaptation were included. In the lack of a single dataset on digital preparedness, these indicators—which comprised simulated values for mobile penetration, broadband access, e-government development index, and innovation score—acted as stand-ins for real digital performance measurements (Yousif & Saini, 2020). These characteristics were chosen because they frequently show up in frameworks for the digital economy that are issued by organizations like the World Economic Forum, OECD, and ITU. To guarantee equal weight during dimensionality reduction and clustering, z-score normalization was used to standardize all numerical variables.

3.2. Dimensionality Reduction Using PCA

The four standardized digital indicators were subjected to Principal Component Analysis (PCA) in order to investigate trends within the multidimensional digital ready space. PCA keeps most of the variation in the dataset while reducing its dimensionality (Kazem et al., 20220). The first two principal components were chosen for additional examination and visualization since they collectively accounted for a sizable amount of the variance. To understand the relative impact of each digital feature on the major components, a PCA loadings plot was also produced.

3.3. Clustering Using K-Means

After dimensionality reduction, countries were grouped into three clusters—Digital Leaders, Transition Economies, and Digital Late Adopters—that corresponded to different levels of preparedness for digital adaption. K-Means clustering was then used. Based on interpretability, conformity with prior research, and empirical separability seen in the PCA space, the number of clusters (k=3) was selected. To improve interpretability, cluster centroids and labels were added to the two-dimensional PCA scatterplot that displayed each nation's cluster assignment (Mussabayev & Mussabayev, 2025).

3.4. Supervised Classification Using Decision Tree

To assess whether GDP alone could serve as a predictor for digital readiness group classification, a Decision Tree Classifier was trained using GDP as the sole feature and cluster labels as the target variable. The decision tree was constrained to a depth of 3 to ensure interpretability and to avoid overfitting. The model’s performance was evaluated using accuracy, precision, recall, and F1-score, providing insights into the ability of traditional economic indicators to proxy for digital maturity.

4. Results & Discussion

Principal component analysis (PCA), K-Means clustering, and decision tree classification were used in this study's machine learning-based digital readiness framework to assess Kazakhstan's standing in comparison to its international peers. A nation's digital infrastructure and policy maturity were represented by four important digital transformation proxies: mobile penetration, broadband access, e-government index, and innovation score.

Digital Leaders, Emerging Economies, and Digital Laggards are three distinct categories of countries that are clearly visible in the PCA-based digital readiness cluster map in Figure 1. Kazakhstan's cluster membership can be visually identified across all PCA components by adding cluster centroids and annotated group labels. Most countries with large GDPs and a focus on innovation were grouped under the Digital Leaders heading, while the other two groups often included countries with laggards and growing infrastructure. The Emerging Economies cluster best describes Kazakhstan, which has demonstrated some successful achievements in digital transformation.

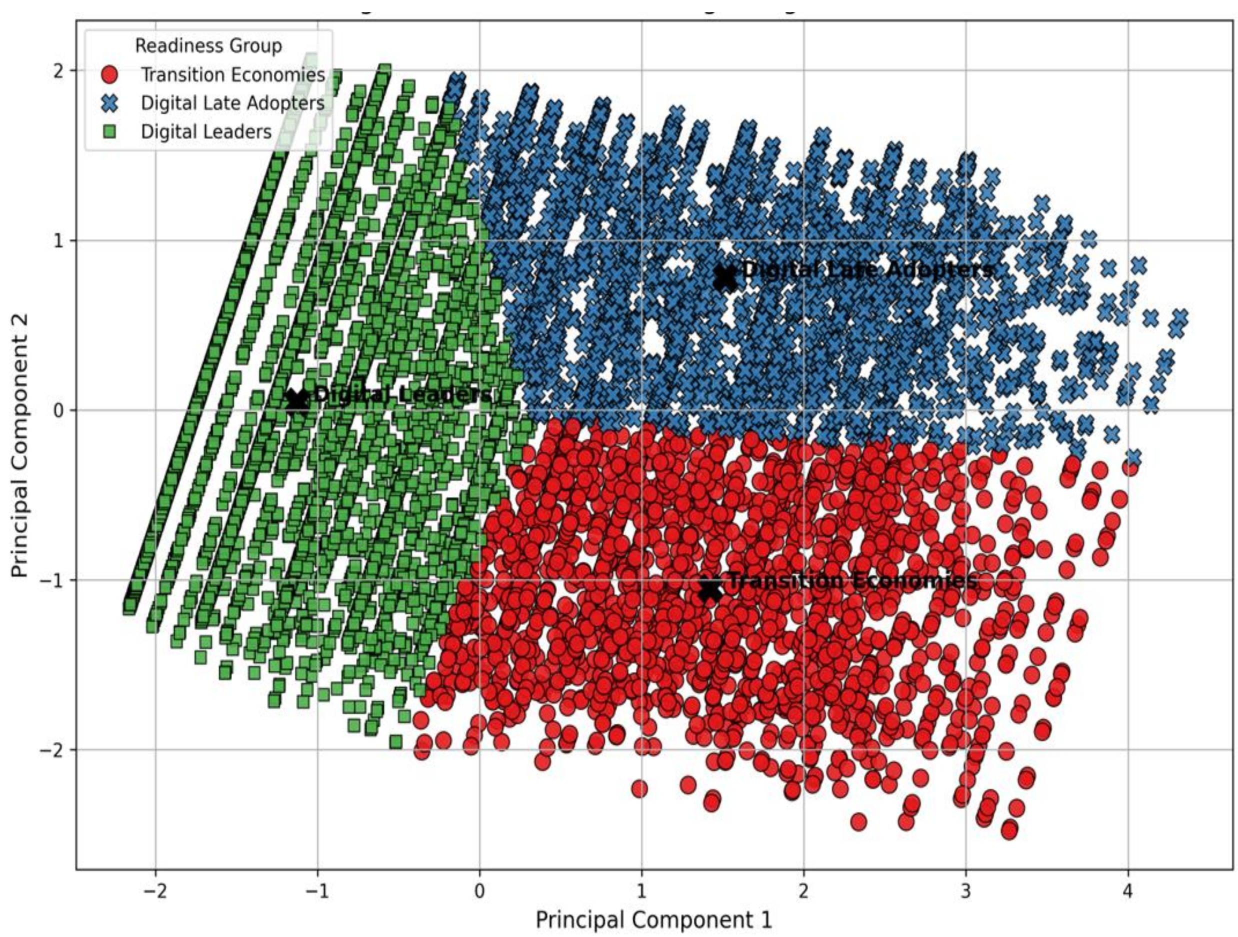

Figure 1: PCA-Based Clustering of Digital Readiness

The scatter plot shows a PCA (Principal Component Analysis) plot of three e-readiness groups: Transition Economies (red), Digital Late Adopters (blue), and Digital Leaders (green). The clusters exhibit some degree of separation along Principal Components 1 and 2, with Digital Leaders being most distinct. Nevertheless, there is a visible overlap between Transition Economies and Digital Late Adopters, specifically on the horizontal axis, indicating shared characteristics and fuzzy boundaries in their digital profiles. The overlap supports earlier findings that GDP alone is insufficient for clear group separation and underscores the need for additional socio-technical variables for better classification and group distinction.

Broadband access and the innovation score contributed the most to the first two principal components, followed by mobile penetration and the e-government index, according to Figure 2, which shows the PCA loadings. This implies that investments in innovative ecosystems and broadband infrastructure could be important catalysts for nations looking to advance from transitional to leading digital maturity.

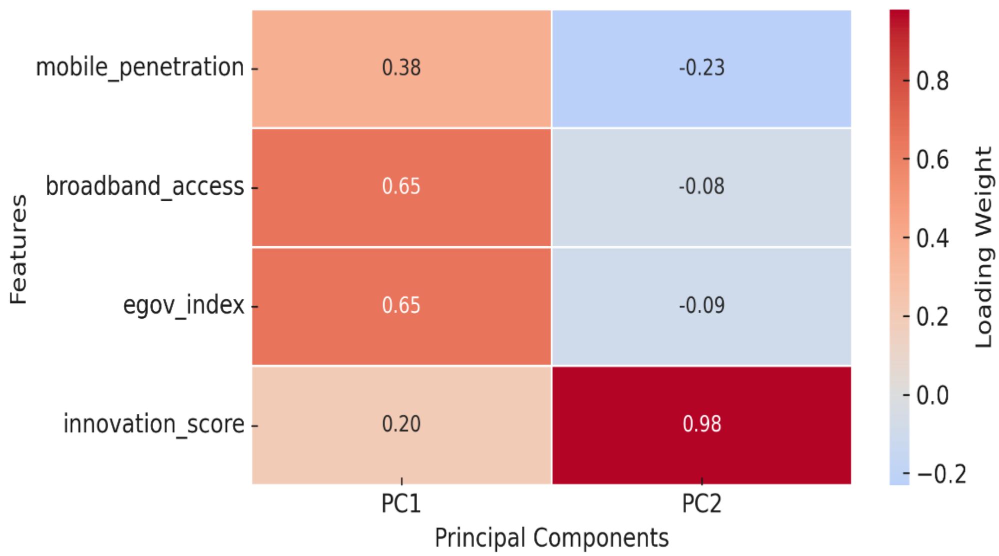

Figure 2: Contribution of Digital Features to Principal Components

PC1 reflects basic digital access and government integration. PC2 emphasizes advanced innovation performance, distinguishing countries with strong R&D and innovation systems. Figure 3 shows the results of the decision tree model trained using GDP as the sole predictor. A decision tree model trained to forecast the digital readiness group with GDP as the only input variable is shown in Figure 4. The three's weighted average F1-score of 0.71 and overall accuracy of 69% show that, despite being useful, GDP by itself is unable to adequately represent the complex nature of digital adaptation. However, the Digital Leaders class's high recall (80%) and precision (99%) demonstrate the model's great sensitivity for recognizing nations with developed digital economies.

When GDP is the only predictor, performance was noticeably worse in differentiating between Transition Economies (F1 = 0.50) and Digital Late Adopters (F1 = 0.46), indicating overlap and ambiguity between these groups. For a more accurate classification, this emphasizes how crucial it is to incorporate socio-technical factors (such as education level, digital policy frameworks, or R&D intensity).

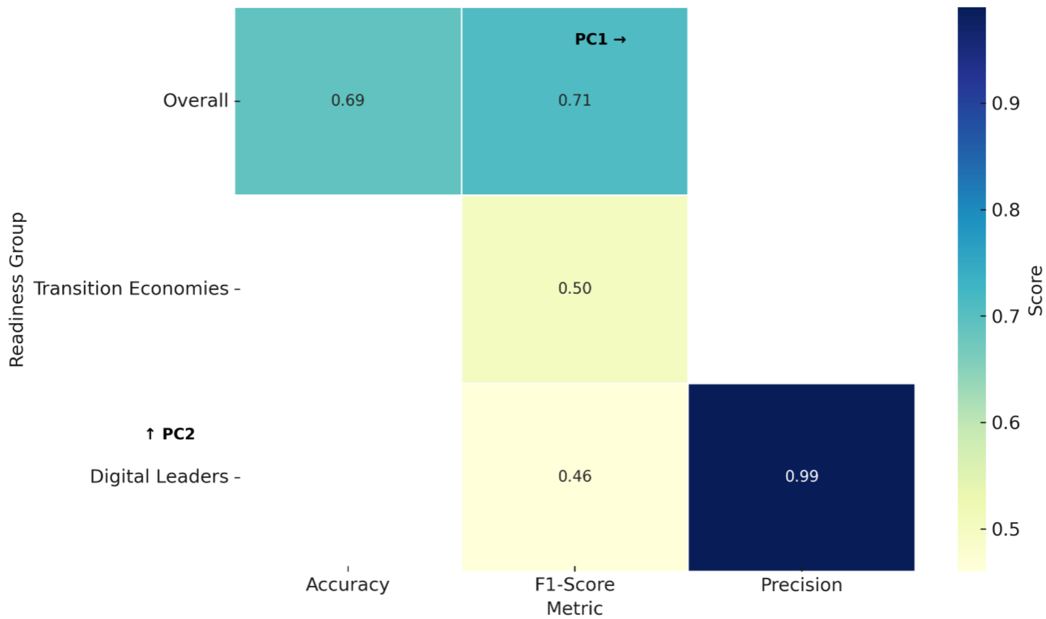

Figure 3: the results of the decision tree model trained using GDP

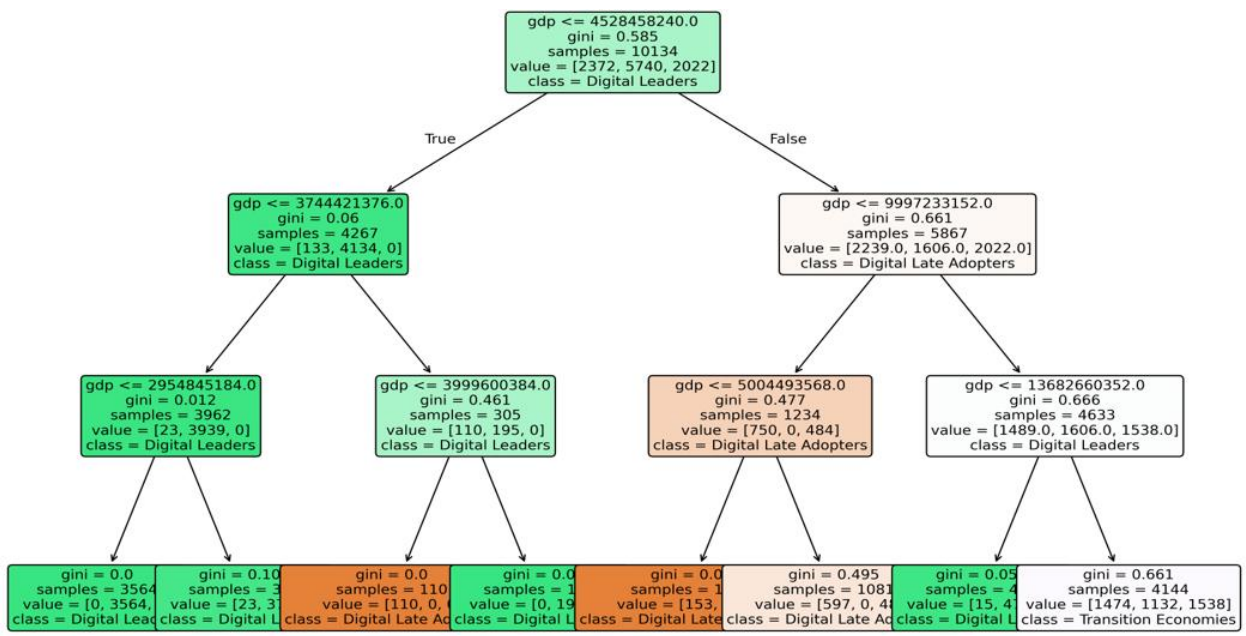

Figure 4: Decision Tree for Digital Readiness Prediction

5. Conclusion

This study's integrated machine learning approach provided a data-driven perspective on the relative maturity of the countries, including Kazakhstan, and effectively divided them into groups based on their level of digital readiness. The results place Kazakhstan in the emerging economies group, showing that despite the progress made, the country still requires continued reform in terms of investment in innovation and improving the quality of the internet. Principal component analysis provided policymakers with practical advice by confirming that broadband availability and innovation score are the two most important differentiators in global digital maturity. However, the classification results based just on GDP show the limitations and predictive power of conventional economic indicators. GDP is a useful tool for identifying digital leaders, but it is not enough to differentiate between digital systems that are trailing behind and those that are emerging.

In conclusion, multifaceted improvements—particularly in innovation systems, infrastructure deployment, and digital policy execution—will probably be necessary for Kazakhstan to move closer to becoming a digital leader. To create a more complex readiness model, future research should incorporate citizen-level data and real-time digital governance measurements. National plans that are in line with the objectives of digital transformation and frameworks for global competitiveness can benefit from these insights.

Acknowledgment
The research leading to these results has received no Research Grant Funding.
Author contribution: All authors have contributed, read, and agreed to the published version of the manuscript results.
Conflict of interest: The authors declare no conflict of interest.

References

[1]. Abusham, E. E. A., & Bashier, H. K. (2013, August). Face recognition using local graph theory (LGT). In 2013 International Conference on Computing, Electrical and Electronic Engineering (ICCEEE) (pp. 593–596). IEEE.
[2]. Abusham, E. A., & Zaabi, A. M. A. (2021). Smartphone application for self-management diabetes: A review. Applied Computing Journal, 25–37.
[3]. Alisharipov, A., Kussainov, K., Yesmagambetov, D., & Arynova, Z. (2024). Elevating citizen engagement in the process of territorial development through digitisation. Digital Government: Research and Practice, 5(4), 1–12.
[4]. Alkishri, W. A. S. I. N., & Al-Bahri, M. A. H. M. O. O. D. (2023). Deepfake image detection methods using discrete Fourier transform analysis and convolutional neural network. Journal of Jilin University (Engineering and Technology Edition), 42(2).
[5]. Alpysbaeva, S. N., Shuneev, S. Z., Bakdolotov, A. A., Beisengazin, K. S., Tautenov, E. I., & Zhanakova, N. N. (2022). Forecast of the long-term trajectory of the potential GDP of Kazakhstan in the context of the global energy transition. Studies on Russian Economic Development, 33(5), 561–570.
[6]. Al-Shibli, A. S., & Abusham, E. (2017). Face recognition using local graph structure and support vector machine (LGS-SVM). International Journal of Computer Applications and Applied Sciences (IJOCAAS), 2(2), 68–72.
[7]. Bissaliyev, M. S., Susi, M., & Shakirov, K. (2025). Convergence between and among the Chinese, the EU and Kazakhstan approaches towards personal data protection against the AI in the digital sphere. Chinese Journal of International Law, 24(2), jmaf011.
[8]. Feher, I., & Fieldsend, A. (2019). The potential for expanding wheat production and exports in Kazakhstan (No. JRC113009). Joint Research Centre.
[9]. Hasanov, F. J., Mikayilov, J. I., Mukhtarov, S., & Suleymanov, E. (2019). Does CO_2 emissions–economic growth relationship reveal EKC in developing countries? Evidence from Kazakhstan. Environmental Science and Pollution Research, 26(29), 30229–30241.
[10]. Igilmanov, N. (2016). Problems of stable development of Kazakhstan. VUZF Review, (1), 40.
[11]. Kandiah, V., Escaith, H., & Shepelyansky, D. L. (2015). Google matrix of the world network of economic activities. The European Physical Journal B, 88, 1–20.
[12]. Kazem, H. A., Yousif, J. H., Chaichan, M. T., Al-Waeli, A. H., & Sopian, K. (2022). Long-term power forecasting using FRNN and PCA models for calculating output parameters in solar photovoltaic generation. Heliyon, 8(1).

[13]. Kuziyeva, G. R., Rakhmatullaeva, D. O., Abdukadoriva, K. A., Babajanova, M. R., Botirova, X. O., & Kaxorova, A. N. (2022, December). Analysis of digital economy performance and economic growth nexus: Case of Uzbekistan. In Proceedings of the 6th International Conference on Future Networks & Distributed Systems (pp. 194–201).
[14]. Mansurov, S., Abdurakhmanov, K., Islamov, B., & Zokirova, N. (2022, December). The application of artificial intelligence in labour economics: Using migration from CIS countries to Russian Federation as an example. In Proceedings of the 6th International Conference on Future Networks & Distributed Systems (pp. 279–284).
[15]. Okolo, C. T., Dell, N., & Vashistha, A. (2022, June). Making AI explainable in the Global South: A systematic review. In Proceedings of the 5th ACM SIGCAS/SIGCHI Conference on Computing and Sustainable Societies (pp. 439–452).
[16]. Ramírez, K. M., Hormaza, J. M., & Soto, S. V. (2020, September). Artificial intelligence and its impact on the prediction of economic indicators. In Proceedings of the 6th International Conference on Engineering & MIS 2020 (pp. 1–8).
[17]. Saini, D. K., Zia, K., & Abusham, E. (2019). Prediction market index by combining financial time-series forecasting and sentiment analysis using soft computing. In Distributed Computing and Artificial Intelligence, 15th International Conference (pp. 180–187). Springer International Publishing.
[18]. Sapakova, S., & Sapakov, A. (2024). Features of modeling the online real estate market in Almaty. Procedia Computer Science, 231, 409–414.
[19]. Shakenova, A. (2018). The role of small and medium enterprises in innovation activities in Kazakhstan= Kis és középvállalkozások szerepe az innovációs tevékenységekben Kazahsztánban. Köztes-Európa, 10(1), 79–86.
[20]. Tjia, L. Y. N. (2022). Kazakhstan's leverage and economic diversification amid Chinese connectivity dreams. Third World Quarterly, 43(4), 797–822.
[21]. Tolesh, F., & Biloshchytska, S. (2024). Forecasting international migration in Kazakhstan using ARIMA models. Procedia Computer Science, 231, 176–183.
[22]. Uteubayev, T., Petrova, M., & Lyubenova, I. (2018, September). Training of qualified specialists in the process of their education in university: The role of the public-private partnership. In CBU International Conference Proceedings (Vol. 6, pp. 491–495).
[23]. Yousif, J. H., & Yousif, M. J. (2023). Critical review of neural network generations and models design. Preprints, 2023091149.
[24]. Yousif, J. H., & Yousif, M. J. (2024). Evolutionary perspectives on neural network generations: A critical examination of models and design strategies. Current Computer Science, 3(1), E050424228693.