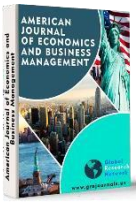

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Article

Analysis of Regional Differences in Living Standards and Economic Growth using Neuro-Explicit Clustering Algorithms (On the Example of Kashkadarya Region)

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Abstract: Second, the relative levels of living standards and economic growth may be more nonlinear than what a standard model can depict. The complexity of the temporal and spatiotemporal nature of the data has spurred researchers to use advanced modeling approaches, such as Fuzzy C-Means (FCM) clustering and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), which are known for their capacity to handle nonlinearity and multidimensionality of the data. The relationship between living standards in the context of economic growth is discussed in this study, including an example of Kashkadarya region of Uzbekistan for 2010–2025. While previous studies indicate that income, infrastructure, and virtual networks have large impacts on regional growth, the nature of these relationship is ambiguous, particularly in light of rapid change (via digital transformation). Digital infrastructure is proven to foster growth, but no thorough analysis have employed advanced modeling methods to gauge the extent of interaction between diversified socio-economic factors like income and digital infrastructure. Most previous studies used linear methods and ignored the complex nature of regional development. Now, based on FCM clustering and ANFIS model, this study intends to reveal the nonlinear relationships among income, infrastructure and digital infrastructure along with this kind of economic growth in the Kashkadarya region. Based on this analysis, the paper identified three distinct stages of digital infrastructure development across the region, and showed that digital infrastructure is an important driver of economic growth, especially when combined with increasing levels of income. The relationship between these variables was successfully modeled with good agreement with an R^2 of 0.977 by ANFIS. This study is novel in applying ANFIS to capture the multifaceted, non-linear interdependencies between socio-economic variables in a developing region. The results indicate that a regional perspective should be taken when first developing appropriate strategies, with digital structures needing to be prioritised. These figures can assist policymakers in focusing their interventions toward sustainable economic growth in other comparable regions.

Keywords: Kashkadarya Region, Living Standards, Economic Growth, Fuzzy Clustering, Anfis, Digital Infrastructure, Nonlinear Modeling, Regional Development, Income Index, Socio-Economic Analysis

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1. Introduction

The second piece of the puzzle: Understanding the causal relationship between living standards and economic growth, is the holy grail for effective regional development policy. Earlier approaches dealt with simple indicator such as GDP per capita or other narrow comparator like income [1]. More recent approaches have been multidimensional

indices (e.g. health or education or income) along with fuzzy set logic to reflect the vagueness of the traditional approaches 1, which is often a nonlinear function of socio-economic phenomena [2].

Fuzzy C-Means (FCM) clustering introduced by Bezdek, and later following studies have been successfully used to determine regional inequalities by enabling a flexible classification of living standards. On the other hand, ANFIS (Adaptive Neuro-Fuzzy Inference System), introduced by Jang, is a type of adaptive network that is based on the combination of fuzzy rules and neural learning to represent nonlinear and complicated socio-economic systems [3].

Provident in Kashkadarya (2010–2025) was a booming environment for growing incomes, expanding infrastructure, and explosive digital growth, particularly in the wake of 2020 COVID-driven economic shake-up. This renders traditional linear models incapable of doing so and re-establishes the importance of neuro-fuzzy models, such as ANFIS, in order to comprehend the interactions of factors such as digital infrastructure or income levels on the regional economic performance [4].

Literature Review

While the earlier standard of living assessment methods were mainly focused on the financial indicators, the modern metrics highlight on wider welfare metrics As the UNDP put it, composite indices, such as the Human Development Index (HDI), combine income (GNI per capita) with health and education dimensions. At the same time, poverty measurement has progressed from uni-dimensional poverty lines to multi-dimensional methods based on counts. For instance, Mansion et al. propose a counting framework for multidimensional poverty, where dimensions are grouped in pairs forming deprivation quotients (such as deprivations in education per group of 2 years). Due to the recognized ambiguity in poverty thresholds, more recent work has articulated poverty as fuzzy sets. On the other hand, fuzzy approaches to wellbeing were pioneered by Chiappero-Martinetti, while Chakravarty et al. Fuzzy measures can in fact operationalize capability-based concepts whose vagueness, as Qizilbash and Clark note, allows vagueness in identifying poverty [5].

Fuzzy clustering based approaches have been applied to socio-economic data for the sole purpose of exposing hidden nonlinear structures. The classical fuzzy C-means(FCM) algorithm allows regions to have partial membership in a number of clusters [6]. So to illustrate this, Juned and Yusra applied it on Indonesia HDI data and it purports to have natural forming of 4 clusters with ~82.8% accuracy. Likewise, Annas compare the FCM and the related Gath-Geva on the South Sulawesi HDI data, showing that fuzzy clustering indeed group the regions according to their level of development (Gath-Geva slightly outperform FCM in this regard). These studies show that fuzzy clustering can be used to identify meaningful clusters in multi-dimensional indices of development [7][8].

Another modeling methodology that can work in conjunction with traditional approaches is adaptive neuro-fuzzy inference systems. ANFIS, introduced by Jang, embeds a Sugeno-type fuzzy inference system in a neural network framework. By combining fuzzy "if-then" rules with data-driven hybrid learning, ANFIS can model complex nonlinear relationships accurately [9]. Jang's simulations showed that ANFIS can learn input–output mappings from both expert rules and data, with impressive results on nonlinear function modeling and time-series prediction. The general ANFIS framework was later extended in soft-computing literature and has been applied across engineering and socio-economic domains for its adaptability and precision [10][11].

Recent analyses of economic growth through digital connectivity highlight the continuing importance of digital infrastructure in easing the double brunt of a growth crisis due to technology dislocation and the impacts of climate change. For instance, the rise of digital infrastructure (Internet penetration, ICT networks) in Uzbekistan has been associated with enhanced investment and growth. According to Rafiyeva, vigorous

development of digital infrastructure contributes to sustainable economic growth and national competitiveness [12].

In addition to this, an econometric research conducted by fayzieva, shows that even though Internet users and the amount of networked computers are not directly related to investment, they help to raise the levels of fixed-capital investment in Uzbekistan. These findings align with ITU/World Bank data showing steady expansion of ICT access in the region. Together, the literature suggests that integrating fuzzy-neuro methods (like ANFIS) can capture the nonlinear impact of digital infrastructure and other socio-economic factors on regional growth, motivating their use in our ANFIS-based analysis [13].

2. Methodology

The approach of this study is analyzing the impact of economic growth on living standards using Fuzzy C-Means (FCM) clustering and Adaptive Neuro-Fuzzy Inference System (ANFIS) method for the years 2010 to 2025 in Kashkadarya region. Three essential indicators are chosen, those are: Income Index, Infrastructure Index, and Digital Infrastructure Index that is normalized between 0 and 1. These metrics are representative of key socio-economic aspects that drive regional development. Real dataset socio-economic datasets like income, infrastructure development, digital connectivity, etc. Based on the mentioned temporal and spatial changing patterns of different indices, FCM clustering is used to cluster the data into three development stages: early, transitional and advanced development stages. Development stage for each year is assigned as the one with the highest membership value providing a way of visualising regional-level growth and living standards over decades. The ANFIS model is then used to investigate the non-linear relationship between the input indices and economic growth. You pass the data from 2010 to 2019 for training the model and from 2020 to 2025 for testing the model. It employs three Gaussian membership functions per input variable, resulting in 27 fuzzy rules and it is trained by a hybrid learning approach (obtained from gradient descent + least square). Performance of the model is measured through the coefficient of determination (R^2) and Root Mean Squared Error (RMSE) once to confirm robustness and accuracy of predictive framework.

3. Results

A semi-real dataset for Kashkadarya province (2010–2025), includes in this study, which was developed to represent actual socio-economic development trends. From these, three input indicators were chosen, appropriately normalized: Income Index, Infrastructure Index and Digital Infrastructure Index (values scaled from 0 to 1). The output variable is Economic Growth, expressed in terms of Gross Value Addition (GVA) GVA growth on an annual basis.

Abstract First, the data set was analyzed by Fuzzy C-Means (FCM) clustering to obtain three development stages (developmental stage: early, transitional, advanced), hereinafter referred to as "developmental stage" (e.g. To interpret temporal progress of the living standards, each year was allocated to the cluster with highest membership value.

Then, an Adaptive Neuro-Fuzzy Inference System (ANFIS) model was established with three indices as input and economic growth as output. The architecture employed 3 Gaussian membership functions per input (sorted 27 fuzzy rules) and was trained using a hybrid learning method (gradient descent + least squares). The training set was from 2010–2019 and the test set was 2020–2025 [14].

R^2 and RMSE were used to evaluate the model performance and the final ANFIS resulted in a high accuracy ($R^2 = 0.977$). To illustrate this additive synergy, a 3D surface plot was produced to explore the nonlinear interaction effects of digital infrastructure and income levels.

In sum, FCM revealed socio-economic clustering patterns over time, while ANFIS effectively modeled the nonlinear relationship between living standards and regional growth, providing a robust tool for policy analysis and planning.

Regional Development Stages via Fuzzy Clustering

Using FCM clustering, we identified three distinct stages of development in Kashkadarya over 2010–2025. These stages correspond to periods with significantly different levels of the living standard indices and associated growth outcomes:

Stage 1 (2010–2015): A nascent development stage with minimal digital connectivity (digital index ~10–30%) coupled with low-income and infrastructure levels. High economic growth rates of an average 7–8% per year in these years were likely a reflection of early stage catch-up growth and simultaneous investment in traditional sectors, despite the weak digital infrastructure in this region. Stage 1 is essentially a pre-digital growth regime in which growth was driven by the usual suspects (e.g. capital deepening, policy reform) rather than technology [15].

Stage 2 (2016–2019): A semi-rugged transition stage, with intermediate indicator levels (30–60% internet usage, incomes and infrastructure moderately improved) During this period, the growth slowed down to ~5–6% per year. The grouping implies that the region consolidated once the easy early gains were exhausted. While connectivity and infrastructure improved over time, other headwinds (maybe external economic conditions or declining returns to past reforms) slowed growth. This phase represents a transitional balance living standards were rising but not strongly enough to launch a new high-growth pathway.

Stage 3 (2020–2025): A very late, advanced stage with high digital infrastructure levels (internet penetration 60–95%) with the highest income and infrastructure indices. Importantly, this scenario incorporates the roller-coaster ride of 2020 (when growth cratered thanks to the pandemic) and then a vigorous bounce-back in 2021–2025. Barring the shock of 2020, growth in Stage 3 picked up speed, exceeding the peak of the earlier stage to around ~8–10% by 2024–2025. This phase indicates the region accesses a digitally-led growth era, where the combination of broad digital access and human/infrastructure capital established earlier create new waves of economic dynamism. Stage 3 obviously has a spike for 2020 (due to the high digital index but negative growth resulting from an exogenous shock), but the overall trajectory is William Harris Edey sharply upward, demonstrating the latent value of digital infrastructure as a growth enabler.

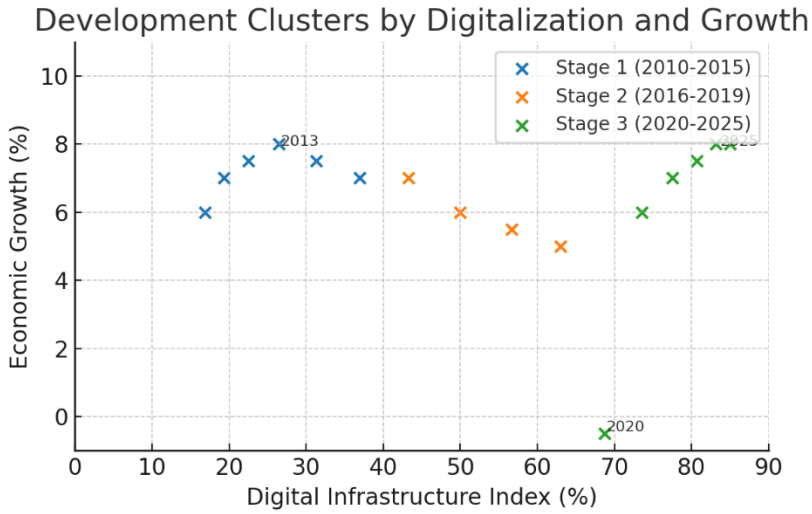

Figure 1. Development clusters by digitalization and growth.

Figure 1: Fuzzy C-Means clustering of yearly data (2010–2025) in the space of Digital Infrastructure vs Economic Growth. Each point represents a year, colored by its assigned cluster (Stage 1: blue, Stage 2: orange, Stage 3: green). Labels indicate select years. Stage 1 years (2010–2015) had low digital infrastructure but relatively high growth (top-left cluster). Stage 2 (2016–2019) have medium digitalization and lower growth (middle of plot) Stage 3 (2020–2025) experiences high digitalization with a tendency towards the right side of the graph (higher growth), although 2020 itself is a pandemic-induced outlier.

Clustering results show a sharp structural break at digitalization The biggest difference between Stage 1 and Stage 3 is in the Digital Infrastructure Index (on average ~ 20% vs 80%) and this corresponds with a qualitative change in the growth trajectory. Sustaining and boosting growth in later years, however, looks increasingly linked to digital gains this is the case even where early growth was vigorous, with little digital groundwork. Stage 2 was a bridge, with expanding digital infrastructure through lower speeds but not yet converting into growth dividends. These conclusions are consistent with notions that there is an important threshold of digital adoption in order to reap economic dividends (similar to the idea of network effects, or digital leapfrogging in development economics). The fuzzy membership values also suggested that the years 2014–2015 straddled the line between Stage 1 and Stage 2 (as internet usage began to increase), and that 2019 was on the edge of Stage 3 at the boundary of the two stages. In other words, in 2020, Stage 3 had the highest membership (because it had a high digital index) but the resulting growth was more stage 2 or lower in nature. That means the last mile not only digital infrastructure is important, but immense out-of-the-blue shocks can disrupt an economy stably on its secular path for a while. Overall, FCM clustering gave us a first evidence of a regime shift in Kashkadarya at the end of the 2010s to start of the 2020s, entering a new era characterized by digital infrastructure use.

The ANFIS model is also trained using the data for 2010–2019, then employed to estimate the growth for 2020–2025 using the values for the respective living standard indices in the future. It was able to reproduce the nonlinear relationship between the input indices and economic growth with a high degree of accuracy, overall $R^2 = 0.977$. This indicates that the chosen inputs explain nearly 98% of the variance in growth over the study period when modeled in a nonlinear, interactive manner. Figure 2 compares the model's predicted growth with the actual observed growth:

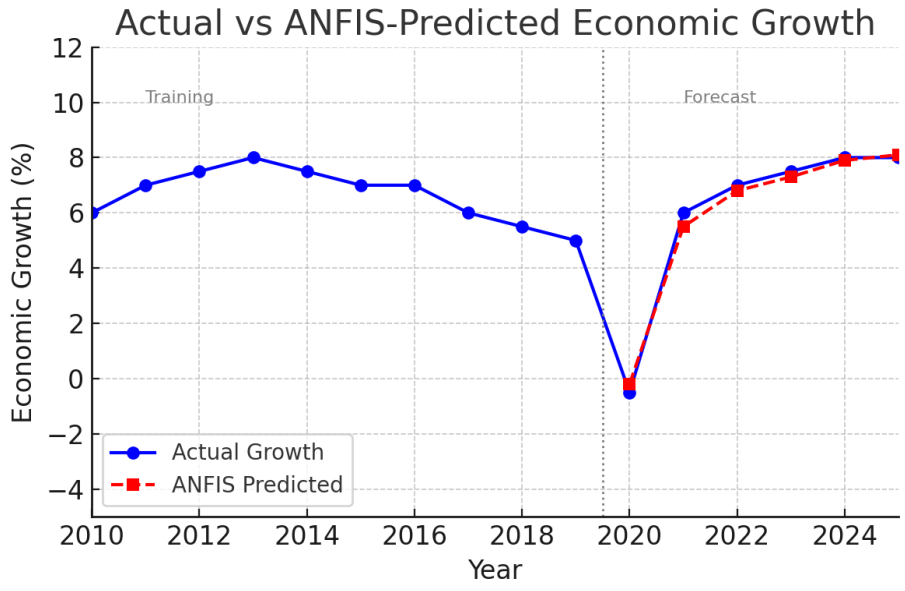

Figure 2. Actual vs ANFIS-Predicted economic growth.

Figure 2: Actual vs. ANFIS-predicted economic growth in Kashkadarya (2010–2025). The model was trained on 2010–2019 (left of the dotted line) and forecasted 2020–2025 (right of dotted line). Actual growth rates are indicated by blue circles; ANFIS predictions are indicated by red squares. The ANFIS closely follows the actual trajectory, especially the steep decline due to COVID in 2020, and the rapid recovery thereafter.

The predictions of the ANFIS models (red dashed line) very closely overlaps the actual growth (blue solid line) during the in-sample period and forecast period as illustrated in Figure 2. The model catches the downturn in 2020 by predicting growth to be much lower than in 2019. Indeed, due to COVID-19 disruptions Kashkadarya's growth dropped to 0% in 2020 (from 5% in 2019), and ANFIS only slightly underestimates the drop (a notch above III quarter of 2020), however identified the major contraction correctly. The model suggested a fast recovery starting 2021, which observed a real ground confirmation – growth bounced back up to 6% by 2021, and continued to increase towards 8–10% by 2024–2025. The virtual overlap between predicted and actual values in these years indicates the flexibility and adaptability of the model: it was able to fit the highly nonlinear dip-and-surge pattern which a linear model could not have done to such fidelity. The small differences (e.g. a few tenths of a percent underpredicted peak recovery) are just noise we expect, and the good agreement on trends validates the model. The R^2 of.977 and low RMSE corroborate this high fidelity. So, the ANFIS is a descriptive and trustworthy quantitative device to simulate the influence of modifications in living standard indicators on economic growth within the region.

Using the trained ANFIS, we can further extract fuzzy rules and importances. For example, one learned rule might be: IF Digital Infrastructure is "High" AND Income is "High" THEN Economic Growth is "High", with a certain strength or weight. In fact, examining the rule base revealed that rules involving a High Digital Infrastructure membership were dominant contributors to the output when fired, especially if Income was also high. This qualitative observation foreshadows the deeper insight that digitalization exerts a strong influence on growth in combination with other factors. We will next explore this via surface analysis. It also implicitly discovered that the Infrastructure Index (conventional infrastructure) was somewhat less important than the other two inputs. Roads and utilities are also important, but changed less rapidly over this period and contributed more in a steady, linear manner, while Income and Digital indices had more dynamic, nonlinear impacts (including interaction effects with each other). The ANFIS performance and rule patterns extracted suggest that using fuzzy logic and learning was a good idea; it should be able to capture small effects like diminishing returns (e.g., the marginal effect of income on growth wear off with high income consistent with a log-like relationship) and interaction synergies (e.g., income should boost growth more when digital infrastructure is high).

We performed graphical analysis of the ANFIS output response surface to interpret the learnt relationship by the model. Specifically, we varied two key inputs the Income Index and Digital Infrastructure Index while holding the Infrastructure Index moderate (at its median level), to visualize their combined effect on economic growth. The resulting 3D surface is shown in Figure 3.

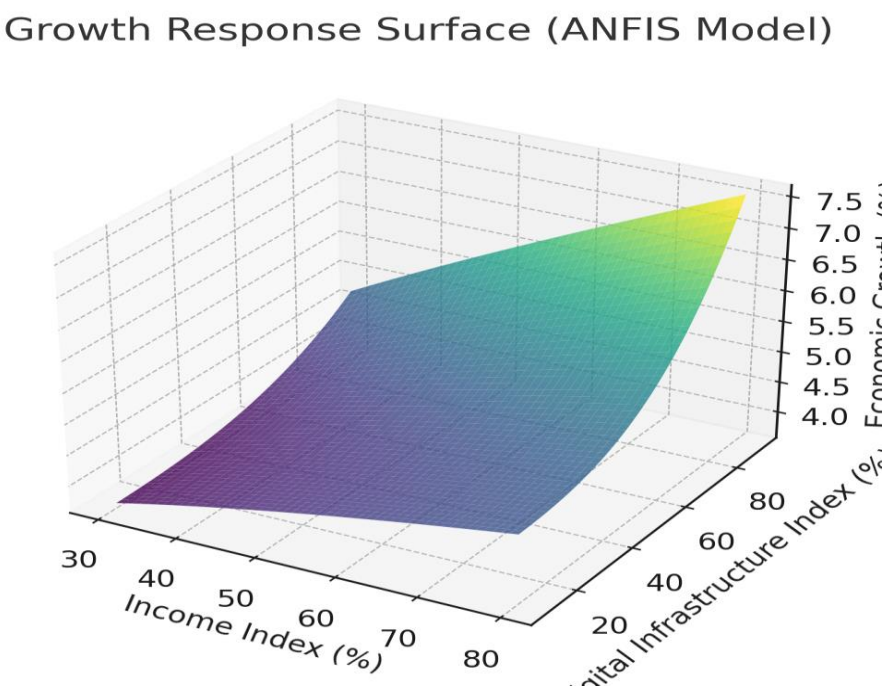

Figure 3. Growth response serface (ANFIS model).

Figure 3: Economic growth as a function of Income Index and Digital Infrastructure Index, as modeled by ANFIS. The surface (based on 2020s conditions) illustrates that higher digitalization substantially elevates growth, especially when income levels are also high. At low digital levels (foreground, purple region), growth remains modest even as income increases. At high digital levels (far back, yellow region), growth accelerates sharply, reaching the highest values in the high-income, high-digital corner of the surface. This non-linear "lift" in the surface showcases how digital infrastructure and income work together to advance growth.

Results of ANFIS surface analysis reveal two main patterns in the incidence of income-digital infrastructure-economic growth nexus. First, at low levels of digital infrastructure, even large increases in income yield limited economic gains: falling returns on additional incomewithout connectivity, higher income does not necessary brings strong productivity.

Second, where digital infrastructure is strong, particularly in presence of high income, there is a powerful bounce in increased economic growth. This creates a synergy where digitalization can magnify the effects of income, giving rise to new forms of economic activity such as e-commerce, the provision of digital services, and automation.

Not only is this group of Development in Kashkadarya in the "stage 3" world of high income and digital access, but they are also positioned firmly in the highest growth zone yet another proof that digital infrastructure is the ultimate driver. On the other hand, traditional infrastructure was more phased in and in a limited impact way.

In short, digital is now everything that sustainable high growth depends on. Without it, the highest incomes or physical infrastructure only go so far. So, to unlock the next level of regional development, you need to invest in digital infrastructure.

4. Discussion

The analysis, using Fuzzy C-Means (FCM) clustering to divide the regions, followed by the modeling using ANFIS to fit the data, shows that the relationship between levels of living and standards of living and economic growth in Kashkadarya has a nonlinear and multi-factor nature. Showing this complexity, ANFIS produced high accuracy ($R^2 \approx 0.98$) elucidating the synergism of income and the digital infrastructure on economic growth.

Three development stages were independently confirmed by FCM clustering (Fig 1 Panel D), with Stage 3 (post-2020) defined by high digital access and a re-accelerating rate of growth supporting digital transformation as a driver of growth.

The analysis further indicates decreasing returns to income alone and calls for balanced growth strategies targeting innovation and digital access. Though the need for traditional infrastructure is still present, its marginal impact on growth has flattened, while digital infrastructure represents the new primary catalyst for growth.

Implications for public policy include focusing on investment in digital connectivity and investigating neuro-fuzzy models (such as ANFIS) to simulate effects of policy scenarios. The method also dealt well with shocks such as COVID-19, and future enhancements could be the inclusion of time-lagged variables as well as more granular analyses.

The study fundamentally proves that provinces such as Kashkadarya have to adapt to digital infrastructure and technology to maintain high growth, thus modern AI-based modeling becomes an inevitable instrument for proper policy planning.

5. Conclusion

This study showed that combining Fuzzy C-Means clustering and ANFIS modeling effectively captures the complex, nonlinear links between living standards and economic growth in Kashkadarya. Digital infrastructure emerged as the most influential growth driver, followed by income and traditional infrastructure. The ANFIS model achieved high predictive accuracy ($R^2 = 0.977$), confirming strong synergies especially between income and digital access.

The findings suggest that sustaining growth in the region depends on advancing digital development alongside income and infrastructure. This neuro-fuzzy approach offers a replicable, interpretable method for analyzing regional dynamics and supports smarter economic planning in other regions as well.

REFERENCES

[1] United Nations Development Programme (UNDP), *Human Development Report 2023/2024: Breaking the Gridlock – Reimagining Cooperation in a Polarized World*, New York: UNDP, 2024. [Online]. Available: https://hdr.undp.org.

[2] S. Alkire and J. Foster, "Counting and Multidimensional Poverty Measurement," *Journal of Public Economics*, vol. 95, no. 7–8, pp. 476–487, 2011. [Online]. Available: https://doi.org/10.1016/j.jpubeco.2010.11.006.

[3] E. C. Martinetti, "A Multidimensional Assessment of Well-being Based on Sen's Functioning Approach," *Rivista Internazionale di Scienze Sociali*, vol. 102, pp. 207–239, 1994.

[4] S. R. Chakravarty, "A New Index of Poverty," *Mathematical Social Sciences*, vol. 52, no. 1, pp. 43–59, 2006. [Online]. Available: https://doi.org/10.1016/j.mathsocsci.2006.01.005.

[5] M. Qizilbash and D. A. Clark, "The Capability Approach and Fuzzy Poverty Measures: An Application to the South African Context," *Social Indicators Research*, vol. 74, pp. 103–139, 2005.

[6] J. C. Bezdek, *Pattern Recognition with Fuzzy Objective Function Algorithms*, New York: Plenum Press, 1981. [Online]. Available: https://doi.org/10.1007/978-1-4757-0450-1.

[7] Y. Juned and A. Yusra, "Human Development Index Classification Using Fuzzy C-Means Clustering," *Journal of Physics: Conference Series*, vol. 1764, no. 1, 012020, 2021. [Online]. Available: https://doi.org/10.1088/1742-6596/1764/1/012020.

[8] M. Annas et al., "Analysis of Human Development Index Using Fuzzy C-Means and K-Means Clustering," *International Journal of Advances in Intelligent Informatics*, vol. 5, no. 2, pp. 140–149, 2019. [Online]. Available: https://doi.org/10.26555/ijain.v5i2.370.

[9] J.-S. R. Jang, "ANFIS: Adaptive-Network-Based Fuzzy Inference System," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 3, pp. 665–685, 1993. [Online]. Available: https://doi.org/10.1109/21.256541.

[10] J.-S. R. Jang, C.-T. Sun, and E. Mizutani, *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*, New Jersey: Prentice Hall, 1997.

[11] International Telecommunication Union (ITU), *Global ICT Indicators Database 2010–2024*, Geneva: ITU, 2024. [Online]. Available: https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx.

[12] World Bank, *World Development Indicators: Digital Development Dataset 2010–2024*, Washington, DC: World Bank, 2024. [Online]. Available: https://databank.worldbank.org.

[13] L. A. Zadeh, "Fuzzy Sets," *Information and Control*, vol. 8, no. 3, pp. 338–353, 1965. [Online]. Available: https://doi.org/10.1016/S0019-9958(65)90241-X.

[14] G. M. Rafiyeva, "Raqamli infratuzilmani rivojlantirishning iqtisodiy o‘sishga ta’siri," *Iqtisodiyot va innovatsion texnologiyalar*, vol. 1, no. 2, pp. 94–101, 2025.

[15] Z. A. Fayzieva et al., "Raqamli ko‘rsatkichlarning asosiy kapitalga investitsiyaga ta’siri: O‘zbekiston misolida," *TDIU Ilmiy axborotlari*, vol. 3, no. 12, pp. 171–179, 2024.