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**Conference Paper**

## Clustering Emerging Economies by Broadband Diffusion Trajectories

ITS 33rd European Conference 2025: "Digital innovation and transformation in uncertain times", Edinburgh, UK, 29th June – 1st July 2025

**Provided in Cooperation with:**

International Telecommunications Society (ITS)

*Suggested Citation:* Aravantinos, Elias; Varoutas, Dimitris (2025) : Clustering Emerging Economies by Broadband Diffusion Trajectories, ITS 33rd European Conference 2025: "Digital innovation and transformation in uncertain times", Edinburgh, UK, 29th June – 1st July 2025, International Telecommunications Society (ITS), Calgary

This Version is available at:

<https://hdl.handle.net/10419/331250>

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## Clustering Emerging Economies by Broadband Diffusion Trajectories

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### Abstract

This study utilizes machine learning (ML) techniques to identify critical factors affecting broadband diffusion and its impact on economic growth in emerging economies. A K-means clustering algorithm has been applied to classify 29 emerging and developing economies using factors such as Information and Communication Technology (ICT) infrastructure, broadband adoption, and foreign direct investment (FDI). Several predictive ML models, such as Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), have been employed to assess the economic effects of broadband adoption and the key drivers of digital-driven growth. The analysis reveals the significant correlations between ICT development, broadband penetration, FDI, and economic growth, highlighting the critical role of digital infrastructure and targeted policy interventions in fostering sustainable economic development in emerging economies.

### 1. Introduction and background

The rapid expansion of broadband and ICT infrastructure has become a fundamental driver of economic transformation in emerging economies, shaping productivity, investment flows, and market accessibility. While existing literature highlights the role of ICT in fostering economic growth, traditional econometric models often struggle to capture nonlinear relationships and complex interaction effects specifically in emerging economies. In response, this study adopts a machine learning-driven approach to explore the economic impact of broadband adoption and ICT development, leveraging unsupervised clustering techniques and predictive modeling to uncover deeper insights into digital-driven growth patterns.

Regarding the research questions addressed in this study, we highlight the following: i) How do ICT index, broadband adoption, and FDI levels differ among high-performing and lagging emerging economies, and what impact do these differences have on GDP? ii) What targeted policy interventions can be effectively implemented within each identified cluster to enhance digital infrastructure, investment, and overall economic growth? iii) How can machine learning algorithms provide some broad variables estimation of the economic growth uptake?

Many researchers have examined the role of ICT in fostering economic growth, often focusing on fixed broadband adoption while overlooking mobile and hybrid broadband effects. (Albiman & Sulong, 2017) demonstrated broadband's significant impact on economic performance in

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<sup>1</sup> The positions illustrated in this article do reflect the personal opinions of the authors and not the official positions of the organizations that the authors are employed to. These official positions of the organizations are presented via their public announcements and official documents such as decisions, etc.

Sub-Saharan Africa. (Appiah-Otoo & Song, 2021) confirmed ICT adoption's role in driving growth across different income levels. Similarly, studies on China (D. Wang, Zhou, Lan, & Wang, 2021) revealed ICT's mixed socioeconomic effects—boosting local economic prosperity while sometimes negatively affecting adjacent provinces. Further analysis by (Badran & Badran, 2011) linked broadband expansion to GDP growth in emerging markets, reinforcing infrastructure investment's critical role in economic advancement. Finally (Aravantos & Varoutas, 2022) is among the few studies that analyzes the factors that influence the diffusion of both fixed and mobile broadband across the OECD countries and have been categorized into five groups based on the stage of innovation, between 1998 and 2015.

Studies have also underscored the strategic role of broadband policies. (Koh, Ong, & Chin, 2024) found that broadband accelerates productivity and innovation in developing nations, while in wealthier countries, it enhances service quality and technological specialization. (W. Wang, Ning, Shu, Riti, & Riti, 2023) demonstrated how ICT development in Africa enhances trade and financial inclusion, advocating for comprehensive digital investment strategies. (Briglauer, Krämer, & Palan, 2024) highlighted broadband's role in productivity and social cohesion, while (Oughton, Comini, Foster, & Hall, 2022) emphasized that affordable 4G and 5G access fosters digital inclusion. (Prado & Bauer, 2021) proposed data-driven broadband policies in Brazil, and (Rath, Panda, & Akram, 2023) identified key ICT convergence drivers in emerging markets.

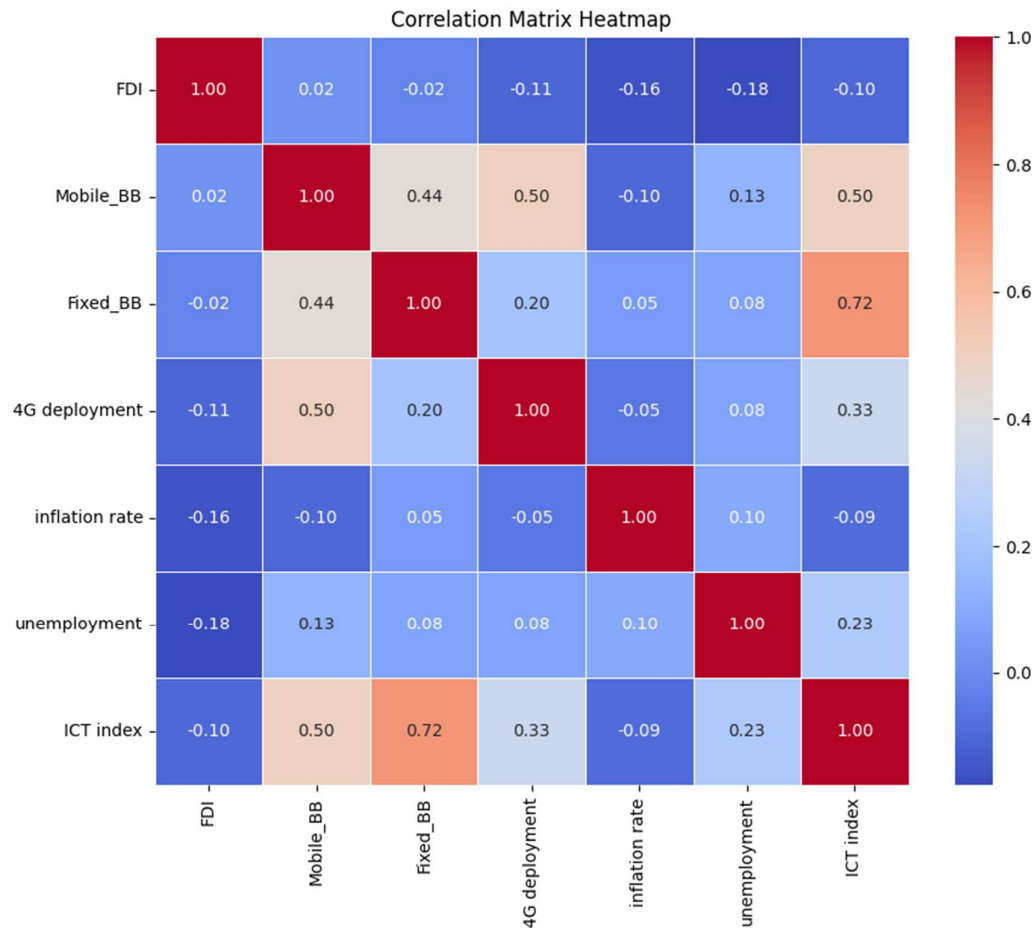
Towards this direction, this study provides a framework for understanding the economic implications of ICT infrastructure by integrating clustering and predictive analytics. Findings emphasize the need for tailored investment strategies, regulatory reforms, and digital inclusion initiatives to maximize broadband's socioeconomic impact across diverse emerging economies.

The remainder of this paper continues in five sections as follows. Section 2 presents the data and the methods of analysis. Section 3 presents and discusses the results. Finally, Section 4 presents the conclusions and future work.

## **2. Data and Methodology outline**

### **2.1. Data**

A panel data collection comprising the 29 emerging and developing nations in terms of broadband adoption serves as the basis for the analysis. The data spans the years 2011 through 2022 and is derived from World Bank, ITU, and UN Trade and Development (UNCTAD) Data Hub. The following variables are included in the study: economic growth (GDP per capita), mobile broadband per 100 subscribers (Mobile\_BB), fixed broadband per 100 subscribers (Fixed\_BB), foreign direct investment (FDI), unemployment, inflation rate, 4G deployment, a dummy variable that varies from 0 to 1 based on the year that 4G was commercially launched per country, and ICT index, an annual frontier technology readiness index developed by UNCTAD. It includes technological capacities related to physical investment, human capital and technological effort, and covers national capacities to use, adopt and adapt technologies such as e-commerce, Chatobot, Artificial Intelligence and 5G.



**Fig 1:** Correlation analysis results in a heat map.

In Fig. 1, three correlations with coefficients around 0.5 are identified. The first correlation is between ICT Index and Fixed BB, with a coefficient of 0.72. This correlation can be explained by the fact that as countries develop their digital infrastructure, fixed broadband tends to improve significantly. The second correlation is between Mobile\_BB and ICT index with a coefficient of 0.50, suggesting that mobile broadband plays an important role, which is expected given the widespread use of mobile technology in emerging markets. The third correlation is between 4G deployment and Mobile\_BB with a coefficient of 0.50. This indicates a moderate positive relationship, meaning that as mobile broadband coverage or usage increases, 4G deployment tends also to increase in these emerging economies. This is a reasonable and expected relationship, as 4G technology typically underpins mobile broadband services. These correlations resonate with observed trends in many emerging economies, where digital infrastructure is often a key driver of economic development, but relationships can vary depending on country-specific factors.

Table 1 illustrated the data summary and descriptive statistics, as below:

Table 1

Data summary and descriptive statistics of the independent variables

Variable	Count	Mean	Std Dev	Min	Max	Std. Dev. /Mean
Year	347	0.501	0.314	0.0000	1.000	0.626
FDI	347	0.291	0.175	0.000	1.000	0.602
Mobile_BB	347	0.340	0.252	0.000	1.000	0.742
Fixed_BB	347	0.151	0.176	0.000	1.000	1.161
Econ Growth	347	0.069	0.128	0.000	1.000	1.864
Unemployment	347	0.177	0.159	0.000	1.000	0.899
Inflation Rate	347	0.110	0.112	0.000	1.000	1.021
ICT Index	347	0.514	0.247	0.000	1.000	0.481
4G Deployment	347	0.694	0.461	0.000	1.000	

## 2.2 Outline of ML methods and tools used

At first, the K-means clustering algorithm—an unsupervised learning technique— has been utilized to classify the 29 emerging countries into distinct groups based on selected features, building upon the approaches outlined by (Teklemariam & Kwon, 2020) and (Ahmed, Seraj, & Islam, 2020). To determine the optimal number of clusters (k), the Elbow method has been utilized, which involves the Within-Cluster Sum of Squares (WCSS) across different values of k number of cluster. The optimal k is identified at the point where the decrease in WCSS begins to plateau, indicating diminishing returns from additional clusters. Beyond the Elbow method, we computed the Silhouette score for each k to evaluate the cohesion and separation of the clusters. To refine our decision, we visually examined the clustering outcomes for the selected values i.e. the number of clusters, by plotting the centroids and assessing the distances between clusters. Further, we performed numerical tests, such as calculating centroid distances, to evaluate the robustness and meaningfulness of each solution. Notably, China was isolated based on our hypothesis into its own cluster (denoted as Cluster -1) due to its unique economic and technological characteristics, which distinguished it from other groups. Based on these analyses, we selected the most reasonable and interpretable number of clusters for subsequent analysis, ensuring that the grouping captured inherent heterogeneity within the data.

In the second part, we investigated 8 models, 4 ML and 4 linear, running the selected algorithms in Python and evaluating the results. The methodology encompasses data loading and cleaning, feature engineering, the training of diverse modeling approaches, comprehensive evaluation, and interpretability analyses. The process elucidates the key contributors to economic growth predictions and offers visual and quantitative insights into feature significance.

Machine learning models are renowned for their adaptability and capacity to capture complex patterns in large datasets. In our study, we leverage this advantage by using four ML algorithms. Four models are based on machine learning techniques: Random Forest, Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Categorical Boosting (CatBoost), The remaining four are linear models: Linear Regression (OLS), Ridge, Lasso, and Elastic Net. (Felix, Alexandre, & Lima, 2025), (Kirgiz, Kiygi-Calli, Cagliyor, & El Oraiby, 2024) and (Herrera, Constantino, Su, & Naranpanawa, 2023).

The models were evaluated for predictive accuracy on the test set using a range of performance metrics, including  $R^2$ , RMSE, MAE, and the Concordance Index.

### 3. Results and discussion

#### 3.1 Cluster analysis

As mentioned, the unsupervised learning algorithm K-means clustering method has been used to classify the 29 countries into different groups. In order to decide on the optimal  $k$ , number of clusters, the Elbow method was adopted (Fig. 2) with calculations of the (Within-Cluster Sum of Squares) WCSS and the Silhouette score.

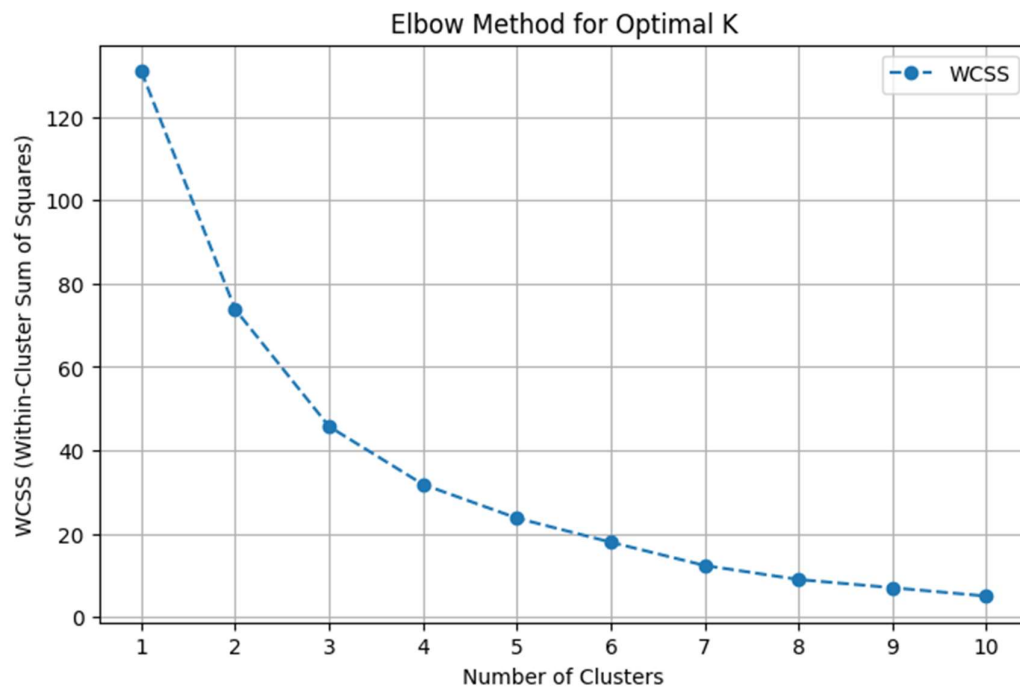


Fig 2: Elbow method

Based on the Elbow method, the 4-clusters scenario ( $k=4$ ) has been selected based on WCSS and Silhouette scores. In more detail, that scenario is acceptable with the following values, WCSS=32.01 and a satisfying Silhouette Score=0.492. As it is obvious in Fig.2, the Elbow point represents the optimal  $K$  value, and that is,  $k=4$ , where adding more clusters results in diminishing returns in terms of reducing WCSS. For example, when  $k=5$ , WCSS=23.58 and for  $k=6$ , WCSS drops to 17.82. The 4-clusters case provides a moderate, reasonable clustering and representation based on the Silhouette score (close to 0.5) (Ling & Weiling, 2025), and is suitable to capture important distinct economic differences. The 4-clusters case also simplifies

clusters' structure, by merging countries into broader groups, that might be easier to study. Based on this selection, Table 2 presents the clusters and the countries within clusters

**Table 2**

**Countries cluster classification for k=4**

<b>Cluster</b>	<b>Countries (K=4)</b>
<b>-1</b>	China
<b>0</b>	Argentina, Egypt, Turkey
<b>1</b>	Bangladesh, Ethiopia, Kenya, Myanmar, Nigeria, Pakistan, Rwanda, Senegal, Tanzania, Uganda, Zambia
<b>2</b>	Brazil, Chile, Malaysia, Mexico, South Africa, Thailand
<b>3</b>	Cambodia, Colombia, India, Indonesia, Morocco, Peru, Philippines, Vietnam

**Table 3**

**ANOVA analysis of variables across clusters (\*\* highly significant  $p < 0.01$ , \* significant  $p < 0.05$ )**

<b>Variable</b>	<b>F-Statistic</b>	<b>P-Value</b>	<b>Significance</b>
Econ Growth	29.634	0.000	*** (Highly Significant)
FDI	4.134	0.005	** (Significant)
Mobile_BB	4.793	0.002	** (Significant)
Fixed_BB	9.502	0.000	*** (Highly Significant)
Unemployment	0.760	0.625	Not Significant
Inflation Rate	20.941	0.000	*** (Highly Significant)
ICT Index	38.890	0.000	*** (Highly Significant)
4G Deployment	6.989	0.000	** (Significant)

Table 3, shows that highly significant variables ( $p < 0.01$ ) include Economic Growth, Fixed Broadband, Inflation Rate, and ICT Index, reinforcing that clusters differ strongly in economic and digital development (Lynch, 2013). FDI, Mobile Broadband, and 4G Deployment are statistically significant, contributing to meaningful cluster distinctions. Unemployment is not significant ( $p = 0.625$ ), indicating that unemployment rates do not vary meaningfully across clusters.

**Table 4 - Average features for each cluster**

<b>KMeans Cluster</b>	<b>Econ Growth</b>	<b>FDI</b>	<b>Mobile_BB</b>	<b>Fixed_BB</b>	<b>Unemployment</b>	<b>Inflation Rate</b>	<b>ICT Index</b>	<b>4G Deployment</b>
<b>-1</b>	0.687	0.230	0.597	0.491	0.129	0.047	0.958	0.833

KMeans _Cluster	Econ Growth	FDI	Mobile_BB	Fixed_BB	Unemployment	Inflation Rate	ICT Index	4G Deployment
0	0.029	0.175	0.402	0.301	0.289	0.269	0.656	0.472
1	0.042	0.262	0.210	0.019	0.133	0.127	0.253	0.594
2	0.042	0.320	0.484	0.272	0.258	0.068	0.762	0.847
3	0.064	0.358	0.368	0.131	0.140	0.068	0.578	0.781

Based on Table 4 and the average features per cluster, we conclude that this clustering analysis reveals a compelling global development spectrum. China emerges as a digital and economic outlier, boasting the strongest performance in growth and tech infrastructure. Cluster 2 countries—like Brazil and Malaysia, both with very high 4G penetration—are digitally maturing, with a high ICT index (adapting also 5G) with a robust foreign investment high mobile adoption and 4G rollout. In contrast, Cluster 0 nations such as Argentina and Egypt face higher inflation and unemployment despite moderate digital access fueled by 4G deployment and mobile broadband. Meanwhile, Cluster 3—including India and Vietnam—occupies a middle ground with expanding connectivity, dominated by mobile broadband and balanced economic indicators. Lastly, Cluster 1 reflects emerging economies in early digital stages, with low ICT scores but potential for mobile-driven growth. Based on these features we attempt to entitle the clusters based on their Economic and Digital Development in Table 5, as below:

**Table 5 - "Economic & Digital Development Clusters"**

Cluster	Title	Countries (K=4)	Description
-1	Advanced Tech Hub	China	Leading technologically advanced economy with high growth and ICT penetration.
0	Transitional Economies with Modest Digital Uptake	Argentina, Egypt, Turkey	Moderate foreign investment and relatively lower broadband infrastructure, indicative of economies in transition with uneven ICT adoption.
1	Emerging Economies with Expanding Mobile Reach	Bangladesh, Ethiopia, Kenya, Myanmar, Nigeria, Pakistan, Rwanda, Senegal, Tanzania, Uganda, Zambia	Growing economies with growing mobile broadband use and decent digital indicators despite challenges in fixed infrastructure and moderate inflation
2	Balanced Middle-Income Digital Adopters	Brazil, Chile, Malaysia, Mexico, South Africa, Thailand	Demonstrate a balanced performance across economic growth, fixed broadband, and ICT



Cluster	Title	Countries (K=4)	Description
3	High-Potential, Rapidly Developing Digital Markets	Cambodia, Colombia, India, Indonesia, Morocco, Peru, Philippines, Vietnam	indicators — not leading, but showing steady, reliable progress
			Economies are dynamic, with improving mobile connectivity and growing ICT ecosystems, despite facing higher unemployment and moderate inflation.

### 3.2 Comparison of Machine Learning vs linear algorithms

As mentioned, ML and linear algorithms has been utilized and compared in order to reveal key contributing factors to economic growth and offer visual and quantitative insights. The results (Table 6 and Fig.3) indicate that among the models evaluated, XGBoost achieved the highest performance with an  $R^2$  score of 0.961, a Root Mean Squared Error (RMSE) of 0.033, a Mean Absolute Error (MAE) of 0.015, and a Concordance Index (C-Index) of 0.852, demonstrating superior predictive accuracy and model fit. CatBoost showed strong performance as well, with an  $R^2$  of 0.838 and a C-Index of 0.754, although its error metrics were higher compared to XGBoost.

**Table 6 Models' comparison**

Model	$R^2$ Score	RMSE	MAE	C-Index
<b>XGBoost</b>	<b>0.961</b>	<b>0.033</b>	<b>0.015</b>	<b>0.852</b>
<b>CatBoost</b>	0.838	0.068	0.027	0.754
<b>LightGBM</b>	0.655	0.100	0.048	0.726
<b>OLS Regression</b>	0.320	0.140	0.076	0.515
<b>Ridge Regression</b>	0.281	0.144	0.075	0.506
<b>Neural Network</b>	0.252	0.147	0.077	0.540
<b>Lasso Regression</b>	-0.005	0.170	0.066	0.500
<b>ElasticNet</b>	-0.005	0.170	0.066	0.500

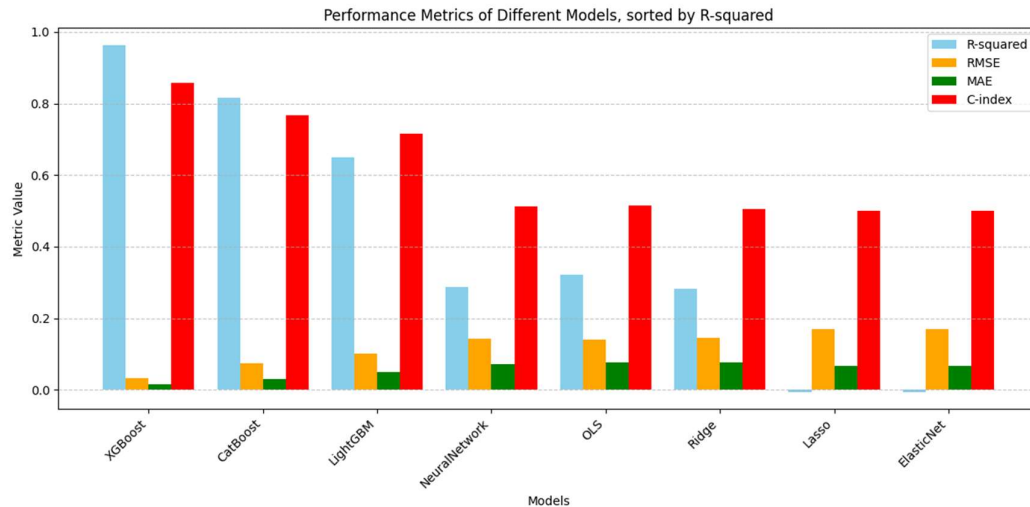


Fig 3: Models' comparison sorted by R-squared

The rest of the models such as LightGBM displayed moderate effectiveness with an  $R^2$  of 0.655 and a C-Index of 0.726, while traditional linear models like Ordinary Least Squares (OLS) and Ridge Regression had substantially lower predictive power, with  $R^2$  scores of 0.320 and 0.281, respectively, and C-Indices below 0.52. Neural Networks performed modestly, with an  $R^2$  of 0.252 and a C-Index of 0.540. Notably, Lasso and ElasticNet regression models exhibited poor performance, with negative  $R^2$  scores indicating limited or no predictive ability in this context. Overall, ensemble gradient boosting methods, particularly XGBoost, provided the most accurate and reliable predictions for the target variable.

To determine the most effective features, we apply the technique from (Ben Jabeur, Stef, & Carmona, 2023), selecting the top features that sustain the model's accuracy above 90% and a threshold greater than 0.01. These features are ranked based on gain-based importance, indicating their significant contribution to reducing model error and enhancing decision splits. But also, weight-based importance, that measures how often a feature is used in decision trees. The threshold rule,  $\text{weight} = 0.01$  means the feature appears infrequently in splits, indicating lower contribution to overall model decisions.

The XGBoost feature selection highlights the most influential factors driving economic growth in emerging economies as illustrated in Fig.4. These findings underscore the critical role of digital infrastructure, foreign direct investment (FDI), and macroeconomic stability in shaping economic performance.

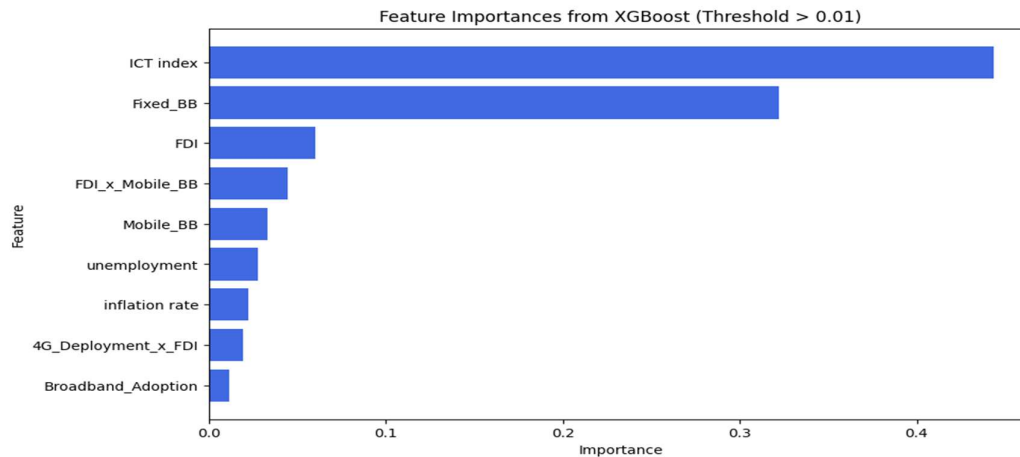


Fig. 4 XGboost important features

Specifically, we can conclude that ICT-driven economies outperform traditional growth models as digital and innovative infrastructure is the most influential growth factor. FDI combined with mobile broadband accelerates market transformation, highlighting the importance of investment-friendly digital policies. Additionally, fixed broadband followed by mobile broadband remains key for economic stability, reinforcing the need for fiber-optic expansion in selected emerging markets that can afford this infrastructure. Unemployment and inflation stability enhance digital adoption, ensuring sustainable technology-driven economic growth.

### 3.3 Analysis and Policy recommendations based on hypotheses

The study posits that high-performing countries exhibit strong GDP, ICT infrastructure, and broadband adoption, whereas lagging clusters struggle with economic and regulatory challenges

- **China:** Advanced ICT investment drives economic growth. Policies should sustain tech leadership, continue upgrading to 5G and beyond, while investing in AI, IoT, and cloud ecosystems, enhance global partnerships, and strengthen digital regulation.
- **Transitional Economies with Modest Digital Uptake:** The cluster of Argentina, Egypt and Turkey demonstrate average levels of foreign direct investment and lagging broadband adoption. To accelerate digital progress, policymakers should focus on stabilizing the regulatory landscape to draw consistent FDI into telecom and digital arenas. Private sector engagement can help towards bridging digital divide and promoting multi-sector ICT integration. Digital governance and consistent regulatory framework can further drive broader adoption and impact.
- **Emerging Economies with Expanding Mobile Reach:** This cluster of countries, comprised of Bangladesh, Ethiopia, Kenya, Myanmar, Nigeria, Pakistan, Rwanda, Senegal, Tanzania, Uganda and Zambia, is characterized by rapid growth in mobile broadband access and commendable progress in 4G network deployment. However, they continue to face limitations in fixed broadband availability and overall ICT development. The combination of low unemployment and moderate inflation points out opportunities in the digital economy. Targeted policy measures towards affordable access, digital literacy and inclusive services can harness this potential.
- **Balanced Middle-Income Digital Adopters:** These countries (Brazil, Chile, Malaysia, Mexico, South Africa, Thailand) exhibit a relatively well-developed digital

infrastructure, particularly in fixed broadband and ICT capabilities, signaling solid progress in connectivity. As maturing digital markets, the challenge is in developing the technological value chain. Policies should pivot from simply expanding access to enhancing the quality and depth of digital engagement. This may include investing in advanced digital skills training, and promoting high-value digital services such as telemedicine, e-government, and smart city innovations. In parallel, policies fostering vibrant innovation ecosystems can stimulate research, entrepreneurship, and locally tech solutions which will help these markets sustain momentum and global competitiveness.

- **High-Potential, Rapidly Developing Digital Markets:** These economies (Cambodia, Colombia, India, Indonesia, Morocco, Peru, Philippines, Vietnam) are dynamic and exhibit strong momentum in mobile connectivity growth, signaling a broadening digital foundation. However high unemployment and moderate inflation prevent inclusive growth and digital progress and ecosystems' development remains unequal. The alignment of ICT policy with social strategies will pave the way for equitable and sustainable digital transformation.

#### 4. Conclusions and Future work

This research provides a comprehensive analysis of the relationship between broadband diffusion and economic growth in emerging economies through clustering analysis and the application of machine learning techniques. By classifying emerging economies into distinct clusters based on their ICT infrastructure, broadband adoption, and FDI levels, the study identifies targeted policy interventions that can enhance digital infrastructure, investment, and overall economic growth within each cluster. The predictive models employed, particularly XGBoost, highlight the critical role of digital infrastructure, FDI, and macroeconomic stability in shaping economic performance.

The analysis based on k-means clustering highlighted the importance of tailored strategies. Distinguishing economies by digital and economic traits enables focused policy and resource distribution. Notably, FDI, Mobile Broadband, and 4G Deployment are statistically significant, contributing to meaningful cluster distinctions, highlighting their key roles in shaping policies, digital and economic landscapes.

Future research should refine these recommendations through cluster-specific policy tuning, targeted policy levers, advanced policy modeling, impact assessments, and analysis of regulatory frameworks to help governments leverage digital investments for sustainable growth. This analysis could also be extended by incorporating additional variables, such as education levels, institutional quality, and specific industry sectors, to provide a more nuanced understanding of the factors influencing digital-driven growth. Furthermore, exploring the impact of different broadband technologies expanding the innovative ICT index, specifically to 5G and satellite internet, on economic development could offer valuable insights for policymakers.

Finally, conducting longitudinal studies to assess the long-term effects of broadband diffusion on economic growth and social inclusion would provide a more comprehensive understanding of the transformative potential of digital technologies in emerging economies.

## Appendix

**Table A1**

List of Countries

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#	Country	#	Country
1	Argentina	20	Philippines
2	Bangladesh	21	Rwanda
3	Brazil	22	Senegal
4	Cambodia	23	South Africa
5	Chile	24	Tanzania
6	China	25	Thailand
7	Colombia	26	Turkey
8	Egypt	27	Uganda
9	Ethiopia	28	Vietnam
10	India	29	Zambia
11	Indonesia		
12	Kenya		
13	Malaysia		
14	Mexico		
15	Morocco		
16	Myanmar		
17	Nigeria		
18	Pakistan		
19	Peru		

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