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Fuzzy Based Evaluation of Digital Connectivity Across Countries Using Mamdani Fuzzy Inference System

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Abstract

Digital connectivity plays an important role in supporting economic growth and social inclusion. However, measuring it across countries is not straightforward because it involves several indicators and a certain level of uncertainty. In this study, we applied a Mamdani Fuzzy Inference System (FIS) to assess digital connectivity in 137 countries. The data were taken from the ITU and World Bank (2024), including Internet Users, Fixed Broadband Subscriptions, and Mobile Cellular Subscriptions. We built a rule-based system using five linguistic categories and adjusted the membership functions based on the data distribution. The centroid method was then used to generate a Digital Connectivity Index (DCI) on a scale of 0 to 100. The results indicate a clear gap in global connectivity. A total of 23 countries achieved a Very High DCI (≥ 80), mostly located in Western Europe and East Asia. In contrast, 17 countries fell into the Very Low category (< 20), mainly from Sub-Saharan Africa. The global average DCI was 53.47. Overall, the proposed approach provides a clear and easy-to-understand classification that can support policy analysis and evaluation of digital development.

Keywords: Mamdani Fuzzy Inference System, Digital Connectivity, Internet Users, Fixed Broadband, Mobile Subscriptions

1. Introduction

Digital connectivity plays a key role in economic growth, promoting social inclusion, and improving access to knowledge around the world (World Bank, 2022). The International Telecommunication Union (ITU) estimates that about 6 billion people or 74% of the world's population were online in 2025, but clear gaps remain between and within countries (ITU, 2024). Measuring these gaps carefully is crucial for creating informed policies that support Sustainable

Development Goal 9, which aims for universal and affordable internet access (United Nations, 2023).

Three indicators from ITU and the World Bank: Internet Users (IU), Fixed Broadband Subscriptions (FB), and Mobile Cellular Subscriptions (MC) are the most widely used proxies for digital connectivity. The nature of these relationships invariably depends on specific ITU-WB indicators because it is inherent in digital ecosystems (Dutta et al., 2022). Countries with very high mobile penetration but negligible fixed broadband, such as many Sub-Saharan African nations, present classification challenges that crisp threshold methods cannot handle adequately (Cariolle, 2021). Cross-country connectivity research has consistently documented a pronounced global digital divide. Raul Katz and Callorda highlighted the positive contribution of broadband expansion to economic performance in Latin American countries, emphasizing the role of digital infrastructure in supporting productivity and growth (Katz & Callorda, 2018). Similarly, Rudra Pradhan et al. identify a bidirectional relationship between mobile connectivity and economic growth in G-20 economies, suggesting that digital development and economic performance reinforce each other (Pradhan et al., 2016). The International Telecommunication Union (ITU) recently released an analysis on the digital divide and is encouraging governments to take action to reduce this gap. Through its partnership with the International Finance Corporation and several other institutions, including Standard Bank, the ITU also supports funding efforts aimed at improving broadband access (ITU, 2024).

This study focuses on evaluating the complex aspects involved in understanding and measuring the impact of the digital divide. It also examines how different factors interact and how individual components relate to each other within the broader global telecommunications system. Because the data used in this study are quite complex, traditional methods may not be sufficient to capture the full impact of the digital divide on society. Therefore, this study uses fuzzy logic as an alternative approach, since it is more flexible and can better handle real-world conditions.

Fuzzy logic, introduced by Lotfi A. Zadeh, offers a principled approach to modeling imprecision and uncertainty (Zadeh, 1965). The Mamdani Fuzzy Inference System (Mamdani & Assilian, 1975) is particularly well-suited for multi-criteria classification tasks due to its interpretable IF–THEN rule structure, which closely resembles human reasoning (Ross, 2017). The Mamdani fuzzy inference system consists of four main stages: (1) fuzzification of input variables; (2) rule evaluation using fuzzy antecedents; (3) aggregation of rule outputs using the max-operator; and (4) defuzzification via the centroid method (Klir & Yuan, 1995). This framework has been widely applied in recent studies, including sustainability assessment (Rustum et al., 2020), environmental and ecological evaluation (Liu & Zhang, 2018), environmental risk analysis (Sarkheil et al., 2021), and multi-criteria decision-making systems under uncertainty (Andayani & Fauziah, 2024).

Prior studies have applied Mamdani FIS in various domains, including smart governance and e-government evaluation (Fatima et al., 2018), human development and socio-economic assessment (Setiawati, 2023), healthcare expert systems (Istiadi et al., 2022), and decision support systems for multi-criteria selection problems (Triwinanto et al., 2023), (Pratama et al., 2021). In digital and ICT-related contexts, fuzzy-based approaches have been widely applied to handle uncertainty and problems involving multiple indicators. A review covering the past two decades found that fuzzy multi-criteria decision-making methods perform well in dealing with such issues.

These methods have been used in more than 150 journals to address complex problems under uncertain conditions, including applications in technology and engineering (Mardani et al., 2015). Another study grouped multi-criteria decision-making methods in a more systematic way and showed that they can be useful when decisions involve several criteria and expert input. These methods are also considered suitable when the situation is not fully clear or contains some level of uncertainty (Kahraman et al., 2015). Taking together, these studies show that fuzzy inference approaches are suitable for modeling information and supporting decision-making. However, their use in comparing connectivity across countries is still relatively limited, especially when multiple ICT indicators are considered simultaneously.

This study aims to fill that gap by developing a Mamdani FIS with a complete set of 75 rules, covering all possible combinations of linguistic categories across the three input variables. The model is then applied to data from 137 countries based on ITU and World Bank sources. The results are also presented through world maps for each input variable as well as the resulting DCI.
The rest of this paper is organized as follows: Section 2 explains the methodology, Section 3 discusses the results, and Section 4 provides the conclusion.

2. Methods

2.1. Data

The data in this study were obtained from the ITU ICT Indicators Database and the World Bank World Development Indicators (World Bank, 2024), which are widely recognized sources for the selected indicators. For each country, the most recent available data were used, mostly from 2024. Countries with incomplete data for any of the indicators were excluded, resulting in a final sample of 137 countries covering various regions and income levels. A summary of the descriptive statistics is presented in Table 1.

Table 1.

Descriptive satistics of input variables

Variable	Min	Max	Mean	Std.Dev.	Unit
Internet Users (IU)	8.6	100.0	74.2	25.0	%
Fixed Broadband (FB)	0.04	45.58	14.58	13.94	/100 people
Mobile Subscriptions (MC)	34.1	183.7	111.8	32.6	/100 people

2.2. Mamdani fuzzy inference system

The Mamdani FIS follows four sequential steps as illustrated below.

Step 1. Fuzzification. Each input is mapped to five linguistic categories: Very Low (VL), Low (L), Moderate (M), High (H), and Very High (VH) using trapezoidal functions for boundary categories and triangular functions for intermediate ones (Klir & Yuan, 1995). Membership function parameters were calibrated to the empirical data distributions and domain knowledge from ITU (2024):

For Internet Users IU ∈ [0, 100]:

$$\mu\_VL(x)=trapMF\,(0,0,15,30);\ \mu\_L(x)=triMF\,(15,30,50);\ \mu\_M(x)=triMF(35,55,75)$$
$$\mu\_H(x)=triMF\,(60,75,90);\ \mu\_VH(x)=trapMF\,(78,90,100,100)$$

For Fixed Broadband FB ∈ [0, 50]:

$$\mu\_VL(x)=trapMF\,(0,0,2,8);\ \mu\_L(x)=triMF\,(2,8,18);\ \mu\_M(x)=triMF(10,20,32)$$
$$\mu\_H(x)=triMF\,(25,35,45);\ \mu\_VH(x)=trapMF\,(38,45,50,50)$$

For Mobile Subscriptions MC ∈ [0, 200]:

$$\mu\_VL(x)=trapMF\,(0,0,25,50);\ \mu\_L(x)=triMF(25,50,90);\ \mu\_M(x)=triMF\,(70,105,135)$$
$$\mu\_H(x)=triMF\,(120,145,170);\ \mu\_VH(x)=trapMF\,(150,170,200,200)$$

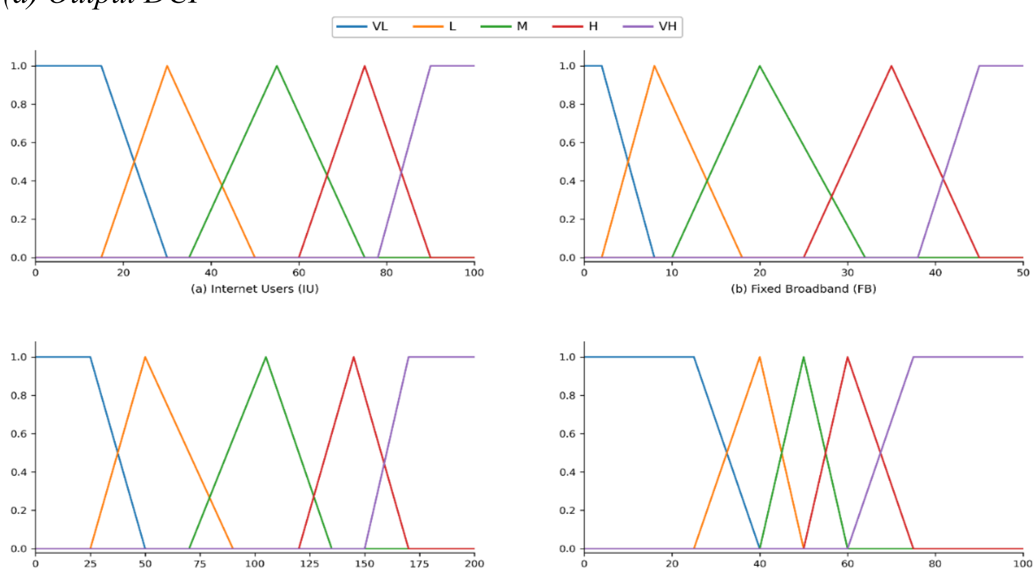
The output DCI ∈ [0, 100] uses the same five categories with symmetric membership functions:

$$\mu\_VL(x)=trapMF\,(0,0,25,40);\ \mu\_L(x)=triMF(25,40,50);\ \mu\_M(x)=triMF\,(40,50,60)$$
$$\mu\_H(x)=triMF(50,60,75);\ \mu\_VH(x)=trapMF(60,75,100,100).$$

All membership functions are visualised in Figure 1.

Figure 1

Membership functions for (a) Internet users, (b) Fixed broadband, (c) Mobile subscriptions, and (d) Output DCI



Step 2. Rule Base. A complete rule base of 75 IF-THEN rules cover all 3 x 5^2 combinations of linguistic input categories. The AND-operator is implemented as the minimum (min) function. The general rule form is:

$$IF\ IU\ is\ A\ AND\ FB\ is\ B\ AND\ MC\ is\ C\ THEN\ DCI\ is\ D$$

Rule design follows three guiding principles based on domain knowledge: (1) IU and FB together are the primary determinants of DCI, when both are VH, DCI is always VH regardless of MC; when both are VL, DCI is always VL; (2) MC serves as a secondary modifier, high mobile penetration in low-broadband contexts (leapfrog scenario) can raise DCI by one category, reflecting the mobile-first internet adoption pattern documented in developing economies(Aker & Mbiti, 2010), (Katz & Callorda, 2018), (World Development Report, 2016); (3) very low MC (VL) with low IU incurs a modest downward adjustment, reflecting poor overall connectivity infrastructure.

Representative rules include:

```
R1:   IF IU is VH AND FB is VH AND MC is VH THEN DCI is VH
R2:   IF IU is VH AND FB is VH AND MC is VL THEN DCI is VH
R3:   IF IU is H AND FB is VH AND MC is H   THEN DCI is VH
R4:   IF IU is M AND FB is VH AND MC is M   THEN DCI is H
R5:   IF IU is H AND FB is VL AND MC is VH THEN DCI is H [leapfrog]
R6:   IF IU is M AND FB is VL AND MC is VH THEN DCI is M [leapfrog]
R7:   IF IU is VL AND FB is VL AND MC is VL THEN DCI is VL
R8:   IF IU is VL AND FB is VL AND MC is VH THEN DCI is VL
... [75 rules total covering all IU × FB × MC combinations]
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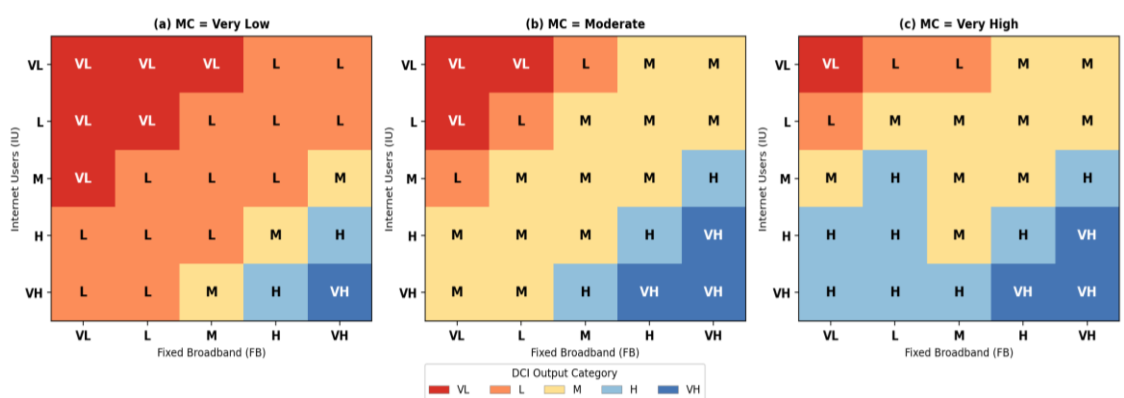
A primarily exhaustive fuzzy rule base augmented with a secondary modification mechanism, where mobile connectivity acts as an adjustment factor capable of elevating the final classification under specific conditions. Figure 2 presents heatmap visualisations of the rule outputs across all IU × FB combinations for three MC scenarios (VL, M, VH), providing an intuitive overview of the complete 75-rule base structure.

Figure 2

Mamdani fuzzy rules output heatmaps (IU rows × FB columns → DCI) three panels show different mobile subscription (MC) levels



The rule base is structured as a set of conditional fuzzy mappings, where the relationship between fixed broadband and internet usage is modulated by the level of mobile connectivity. As shown in Figure 2, higher mobile connectivity systematically shifts the output toward higher DCI categories, reflecting a mobile-driven enhancement effect that enables partial compensation for limited broadband infrastructure.

Step 3. Aggregation. All activated rule outputs are aggregated using the max-operator to produce a unified fuzzy output set, consistent with contemporary formulations of aggregation operators in fuzzy inference systems (Kozielski et al., 2024), (Li & He, 2024).

Step 4. Defuzzification. The centroid method converts the aggregate fuzzy set to a crisp DCI value:

$$DCI = \int \mu\_agg(z) \cdot z\, dz \;/\; \int \mu\_agg(z)\, dz$$

Countries are classified based on the crisp DCI: Very Low (DCI < 20), Low (20 ≤ DCI < 40), Moderate (40 ≤ DCI < 60), High (60 ≤ DCI < 80), and Very High (DCI ≥ 80).

3. Result and Discussion

3.1. Input Variable Distributions

Figures 3 to 5 show maps of three variables. Internet Users (Figure 3) shows a sharp North-South gradient, with European, North American, and East Asian countries exceeding 90%, while much of Sub-Saharan Africa remains below 35%. Fixed Broadband (Figure 4) reveals even steeper concentration, with only Western Europe, East Asia, and North America exceeding 25 per 100, while Africa and South Asia register near-zero values. Mobile Subscriptions (Figure 5) display a more uniform global pattern, with many low-income countries achieving 80 up to 130 per 100, reflecting the mobile first internet access phenomenon (Aker & Mbiti, 2010), (Bala, 2024).

Figure 3

Choropleth map of internet users (% of population) (source: ITU/world bank WDI, 2024)

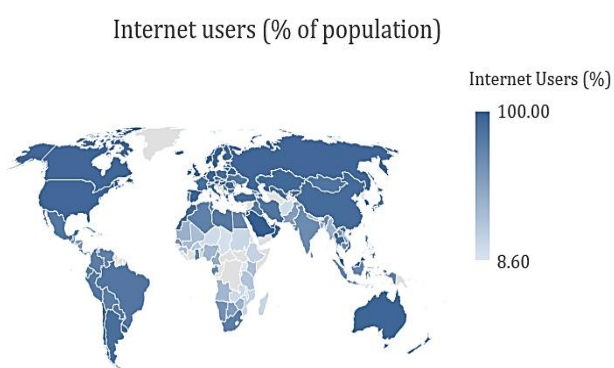


Figure 4

Choropleth map of fixed broadband subscriptions (per 100 people) (Source: ITU/World Bank WDI, 2024)

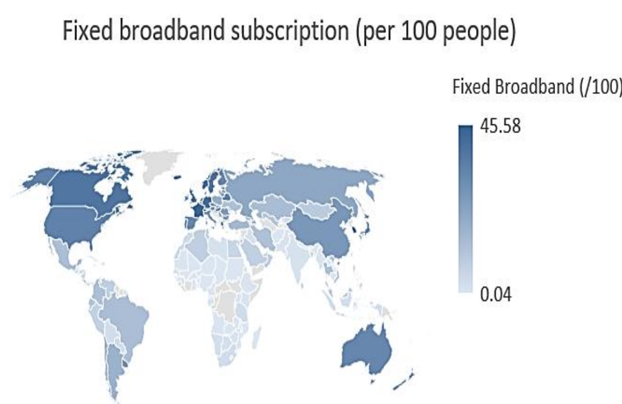
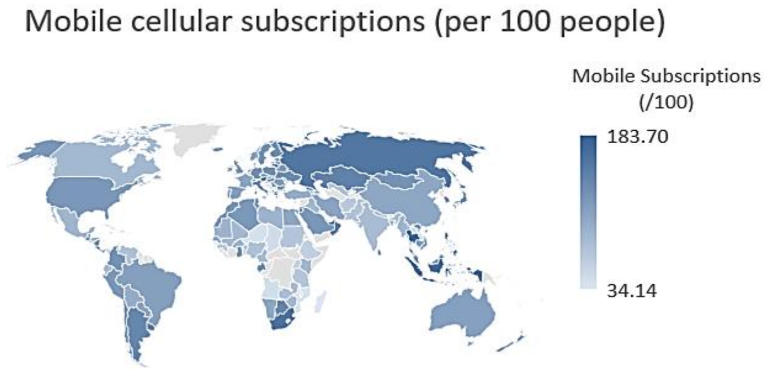


Figure 5

Choropleth map of mobile cellular subscriptions (per 100 people) (Source: ITU/World Bank WDI, 2024)



3.2. Digital Connectivity Index Results

The Mamdani FIS was applied to all 137 countries. Figure 6 presents the DCI choropleth map, Figure 7 ranks the top 20 and bottom 20 countries, and Table 2 reports DCI scores for 22 representative countries selected across all five DCI categories and major world regions.

Figure 6

Choropleth map of digital connectivity index (DCI) classification (Mamdani FIS, ITU/World Bank 2024 with 137 countries)

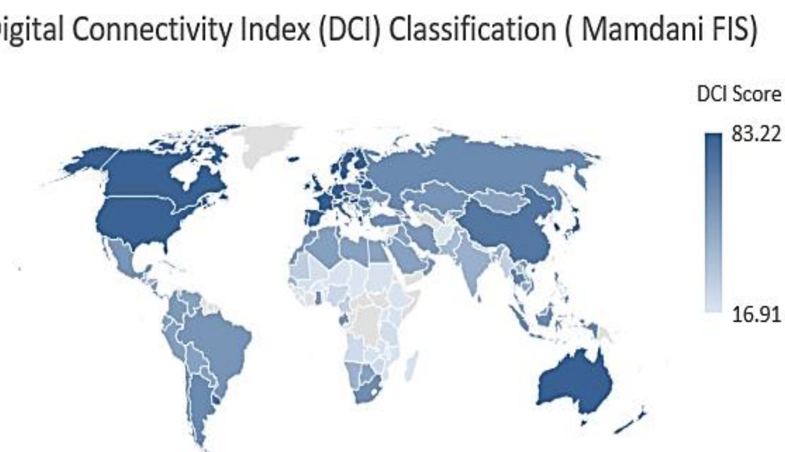


Table 2

DCI Classification for Selected Countries (n = 22 of 137; representative across all categories)

Country	IU (%)	FB /100	MC /100	DCI	Category
South Korea	97.9	45.58	143.21	83.22	Very High
France	88.7	43.75	106.21	82.04	Very High
Norway	99.0	40.23	107.84	81.72	Very High
Canada	94.4	38.01	85.90	81.64	Very High
Japan	85.5	31.68	133.45	77.97	High
Romania	91.3	24.29	114.59	61.82	High
Argentina	89.7	17.78	139.81	61.43	High
Indonesia	72.8	2.29	173.84	60.37	High
Brazil	84.5	13.70	113.00	56.64	Moderate
Vietnam	84.2	11.80	125.62	55.44	Moderate
Colombia	79.3	12.88	126.81	54.25	Moderate
Morocco	91.2	3.86	122.88	53.49	Moderate
Philippines	67.3	3.24	159.40	57.46	Moderate
India	70.0	1.33	80.50	43.40	Moderate
Nigeria	41.2	0.04	75.92	23.65	Low
Pakistan	57.3	0.93	73.36	37.97	Low
Haiti	47.9	0.27	59.07	33.16	Low
Tanzania	31.2	3.22	69.72	20.84	Low
Ethiopia	21.4	0.55	59.66	17.95	Very Low
Niger	15.6	0.04	40.88	17.74	Very Low
Uganda	8.9	0.34	58.21	17.21	Very Low
Chad	12.6	0.07	46.00	17.06	Very Low

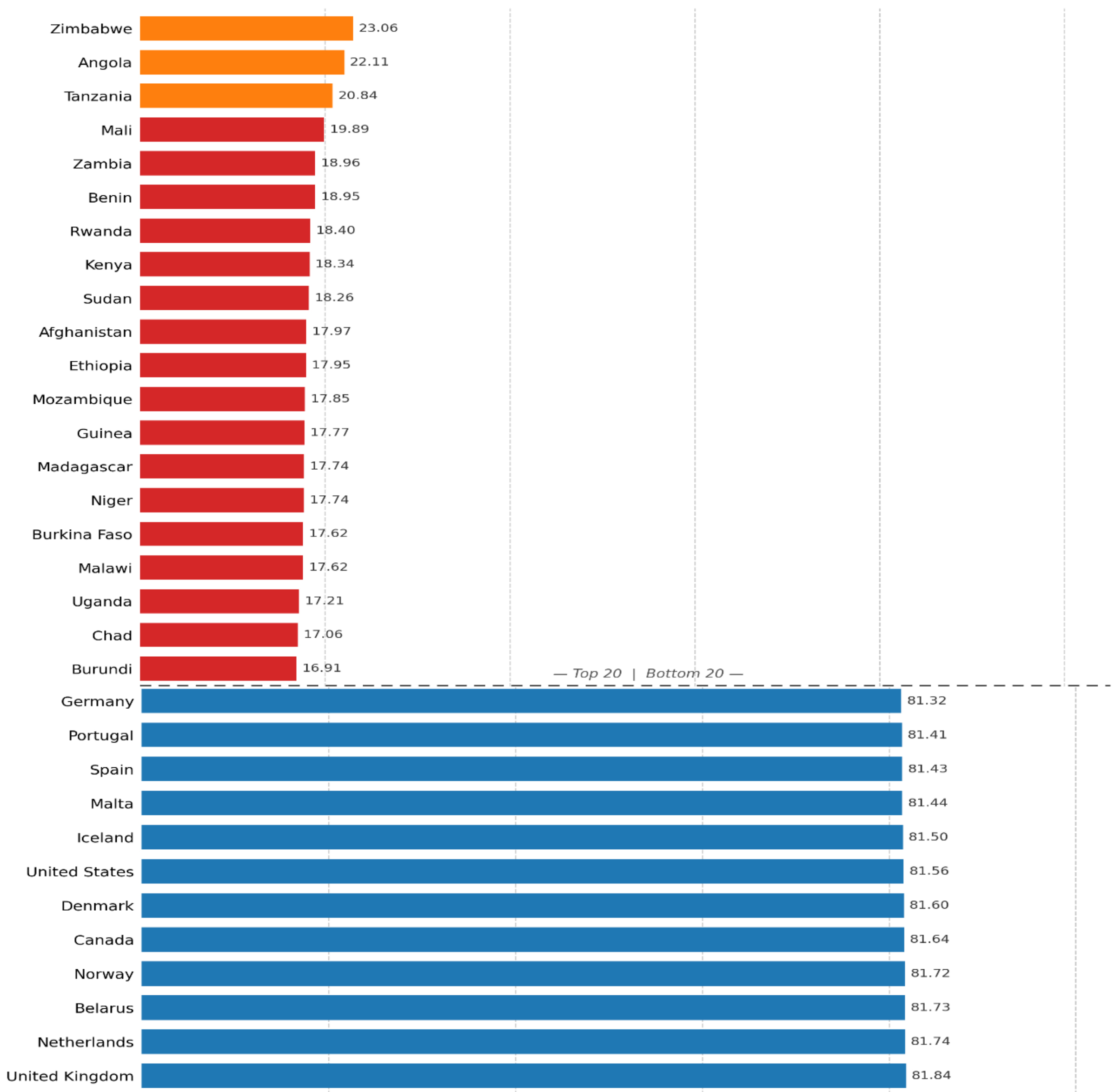
Table 3

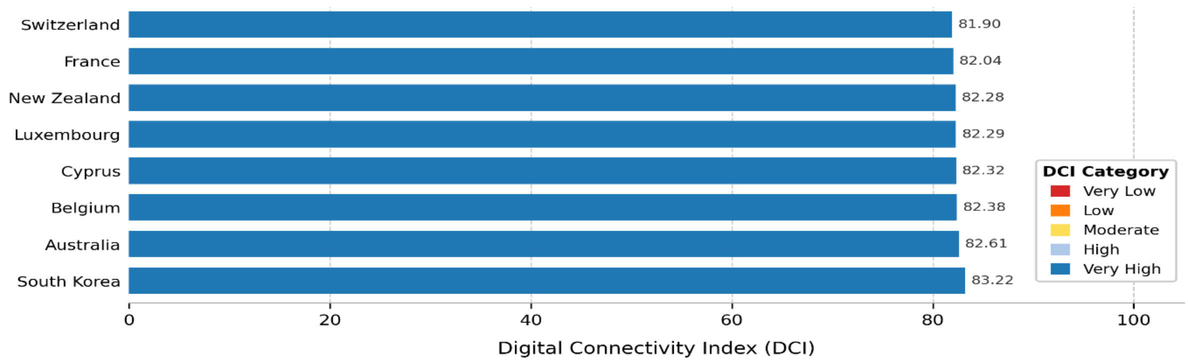
Distribution of 137 Countries by DCI Category

Category	Range	N	%
Very High	≥ 80	23	16.8%
High	60–79	24	17.5%
Moderate	40–59	58	42.3%
Low	20–39	15	10.9%
Very Low	< 20	17	12.4%

Figure 7

Top 20 and Bottom 20 Countries by DCI Score (Pure Mamdani FIS; colour indicates DCI category)





3.3. Discussion

The results from the Mamdani FIS show a clear polarization in the global distribution (Table 3, Figure 6). The 23 countries classified as Very High (DCI ≥ 80) are mainly located in Western Europe and East Asia, which reflects their well-developed fixed broadband infrastructure (FB > 25 per 100) and very high internet usage (IU > 90%). South Korea records the highest score (DCI = 83.22), supported by the highest fixed broadband level observed (45.58 per 100), along with very high IU and MC values.

At the other end, the 17 countries classified as Very Low (DCI < 20) are mostly found in Sub-Saharan Africa. These countries generally have very low fixed broadband levels (FB < 0.6 per 100) and internet usage below 35%. The Mamdani rule base captures this pattern well, showing that even relatively high mobile penetration is not enough to offset low internet adoption and the lack of fixed broadband infrastructure. This is consistent with the logic in rule R8: IF IU is VL AND FB is VL AND MC is VH THEN DCI is VL, which reflects that mobile access alone, without broader internet infrastructure, cannot significantly improve a country's overall connectivity level.

The 58 countries in the Moderate category (40 ≤ DCI < 60) represent the most diverse and policy-relevant group, including several large emerging economies such as Brazil (DCI = 56.64), Mexico (56.12), Vietnam (55.44), and Colombia (54.25). These countries generally show relatively high internet usage but still fall behind in fixed broadband development. As a result, they remain in the Moderate range, where focused investment in infrastructure could help move them into the High category.

Based on the results, one notable case is Indonesia (DCI = 60.37, High), which reaches the High category mainly due to its very high mobile subscriptions (173.84 per 100), despite having low fixed broadband (2.29 per 100). The leapfrogging rule (R5: IF IU is H AND FB is VL AND MC is VH THEN DCI is H) is strongly activated for Indonesia, resulting in a higher DCI compared to countries with similar IU and FB levels but lower mobile subscriptions. This finding highlights the practical importance of including mobile compensation rules, as suggested by the ICT leapfrogging concept (Aker & Mbiti, 2010).

One practical advantage of the Mamdani approach is its transparency. Unlike machine learning classifiers or weighted scoring methods, each DCI value can be clearly explained by identifying which rules are activated and how strong their contributions are. This makes it easier for policymakers to interpret the results. By looking at the rule consequents, they can understand what combination of indicators is needed to move to a higher DCI category. For instance, a country in the Low category can see that increasing internet usage to the Moderate level, while maintaining high mobile subscriptions, could shift its outcomes toward the Moderate range.

4. Conclusion

This study uses a Mamdani Fuzzy Inference System to assess digital connectivity across 137 countries based on ITU and World Bank (2024) data, including Internet Users, Fixed Broadband Subscriptions, and Mobile Cellular Subscriptions. The membership functions were adjusted to match the actual data distribution, and a complete set of 75 IF–THEN rules was developed to represent all possible combinations of the input categories. The rule base is largely exhaustive, with mobile connectivity treated as a supporting factor. The centroid method was then used to generate a Digital Connectivity Index (DCI) on a scale of 0 to 100, which is divided into five linguistic categories.

The results show a clear polarization in global connectivity. A total of 23 countries fall into the Very High category (DCI $\geq$ 80), mainly located in Western Europe and East Asia, while 17 countries are classified as Very Low (DCI $<$ 20), mostly in Sub-Saharan Africa. The largest group is the Moderate category, with 58 countries, including several major emerging economies. Overall, the average DCI is 53.47, with values ranging from 16.91 to 83.22.

Based on the results, including mobile connectivity as a secondary factor helps improve classifications in certain cases, especially in countries with limited fixed broadband infrastructure. This pattern can be seen in countries such as Indonesia and the Philippines, where high mobile penetration partly offsets low broadband availability, in line with the leapfrogging concept reflected in the rule base. In addition, the Mamdani approach offers a high level of transparency, since each classification can be traced back to specific IF–THEN rules. This makes the proposed framework useful for policy interpretation as well as for analyzing digital development.

Future research can expand the set of variables by including indicators such as digital skills and affordability. It could also explore the use of type-2 fuzzy sets to better capture higher levels of uncertainty. In addition, applying the model over time would allow for the analysis of changes in digital connectivity. Another potential direction is to integrate the DCI into broader composite development indices for more comprehensive evaluation.

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