

Clustering Countries by Central Bank Digital Currency (CBDC) Readiness

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Abstract

The global landscape of Central Bank Digital Currency (CBDC) development is fragmented and progresses at varied speeds, with motivations ranging from improving financial inclusion to increasing monetary policy efficiency. This study addresses the lack of a quantitative classification framework by creating an empirical typology of national CBDC readiness. We compiled a comprehensive dataset for 124 countries, integrating key indicators of financial inclusion from the World Bank's Global Findex database with digital infrastructure metrics from the ITU and UN. Using unsupervised machine learning, specifically K-Means clustering, DBSCAN, Silhouette Score, and Principal Component Analysis, we segmented these nations into distinct groups. The analysis reveals four clear archetypes: "Leaders" with high capacity and active pilots; "Contenders" with high capacity but a cautious research stance; "Emerging Adopters" driven by financial inclusion goals; and a "Watchlist" where foundational development is a priority. This research provides a novel framework that moves beyond descriptive trackers, empirically demonstrating the crucial divergence between technical capability and policy action. The resulting typology serves as a practical benchmarking tool for policymakers to situate their nations and identify peer countries in the evolving digital currency ecosystem.

Keywords: *Cluster Analysis, Financial Inclusion, Digital Infrastructure, Country Readiness, Digital Currency.*

JEL Classification: E58, E42, O33, G21, C38

Introduction

For centuries, the story of money has been about moving from physical things, like coins and paper bills, to digital ideas, like credit cards and payment apps. Now, governments around the world are getting ready for the next big step: creating their own official digital currencies, known as Central Bank Digital Currencies, or CBDCs.

Think of it as a digital version of the cash in your wallet, issued and backed by the government, just like traditional money.

Suddenly, it seems like every country is talking about this. You hear about China running huge pilot programs for a "digital yuan," while countries like Sweden are deep into testing. At the same time, you hear that the United States and the United Kingdom are still in the early research stages, moving much more slowly. Meanwhile, dozens of other nations are somewhere in between.

With all this activity, it's easy to get lost. It feels like a global race has started, but nobody is quite sure who is in the lead, who is just warming up, and who hasn't even made it to the starting line.

We wanted to create a clear map of this new and confusing landscape. Instead of looking at countries one by one, we decided to step back and see if we could find a pattern. We gathered a massive amount of data from all over the world things like how many people have a bank account, how many use the internet, how advanced each government's digital services are, and how common digital payments have become.

Our main question was simple: If we feed all this information to a computer, can it sort the world's countries into logical groups based on how ready they truly are for a digital currency?

The answer is yes. This paper will walk you through how we did it. We will show you how the world neatly divides into four distinct groups from the trailblazers who are already building the future, to the cautious giants who are carefully planning their next move, and the emerging nations who see a golden opportunity to leap forward. This isn't just a story about technology; it's a story about the different roads countries are taking to build the next generation of money.

2. Literature Review

Bank for International Settlements (BIS) (2023). *Embracing diversity, advancing together – results of the 2023 BIS survey on central bank digital currencies and crypto*.

Key Contributions: Provides the most comprehensive, up-to-date global overview of central bank CBDC efforts, motivations, and design choices. Confirms that work is "fragmented" and proceeding at "varied speeds."

Relevance to My Paper: Establishes the core premise that the global CBDC landscape is fragmented and heterogeneous, directly validating the need for an empirical classification system.

Tobin, J. (1985). *Financial Innovation and Deregulation in the U.S. Banking Industry*.

Key Contributions: Articulated the idea of "deposits at the Fed" or "reserves for all," laying the theoretical groundwork for central bank digital money as a safe public liability.

Relevance to My Paper: Provides the foundational theoretical justification for the CBDC concept, linking it to the central bank's core mandate and the policy goals of the "Contenders."

Auer, R., and Böhme, R. (2020). *The technology of retail central bank digital currency*.

Key Contributions: Systematically analyzes the fundamental technical design trade-offs of CBDC systems (e.g., centralized vs. DLT, token-based vs. account-based) and links them to policy goals.

Relevance to My Paper: Provides the technical and conceptual foundation for the "technical capability" dimension, framing the complexity that "Leaders" and "Contenders" must solve.

Brunnermeier, M. K., and Niepelt, D. (2019). *The central bank digital currency and the future of monetary system*.

Key Contributions: Uses macro-economic models to analyze the potential effects of CBDC on bank balance sheets and financial stability, particularly the risk of bank disintermediation (bank runs).

Relevance to My Paper: Helps define the cautious policy stance of the high-capacity "Contenders," whose primary motive for delay is mitigating financial stability risks.

Mishra, A., and Prasad, E. S. (2021). *Central Bank Digital Currency and the Future of Monetary Policy*.

Key Contributions: Examines the potential for CBDC to enhance the scope of monetary policy tools (e.g., negative interest rates) and its implications for monetary transmission.

Relevance to My Paper: Reinforces one of the key explicit policy motivations mentioned in the abstract—"increasing monetary policy efficiency."

Demirguc-Kunt, A., et al. (2022). *The Global Findex Database 2021: Financial Inclusion, Digital Payments, and Resilience in the Age of COVID-19*.

Key Contributions: Presents demand-side data on financial access and usage (account ownership, digital payments) across 148 economies.

Relevance to My Paper: Serves as the primary data source for the Financial Inclusion pillar, empirically defining the social goal that drives the "Emerging Adopters" archetype.

International Telecommunication Union (ITU) (2023). *Measuring digital development: Facts and Figures*.

Key Contributions: Compiles authoritative global statistics on digital infrastructure and connectivity (e.g., mobile-cellular subscriptions, internet access, broadband access).

Relevance to My Paper: Serves as the primary data source for the Digital Infrastructure pillar, providing objective metrics for national "technical capability."

United Nations (2022). *E-Government Survey: The Future of Digital Government*.

Key Contributions: Provides national data on Digital Public Infrastructure (DPI), digital service delivery, and the institutional capacity for government digitalization.

Relevance to My Paper: Complements ITU data by providing an indicator of institutional technical capacity, strengthening the overall "capability" score for nations like the "Leaders."

G20 (2021). *Roadmap for Enhancing Cross-border Payments*.

Key Contributions: Outlines the global policy push to reduce the cost and increase the speed of cross-border payments, listing CBDCs as a key potential solution.

Relevance to My Paper: Provides context on the global policy environment, highlighting an advanced motive that distinguishes "Leaders" (often focused on wholesale CBDC) from domestic "Emerging Adopters."

Atlantic Council GeoEconomics Center (2023). *Central Bank Digital Currency Tracker*.

Key Contributions: A frequently updated public resource that descriptively tracks the stated development stage (e.g., research, pilot, launched) of CBDC projects globally.

Relevance to My Paper: Represents the "descriptive trackers" that the study explicitly seeks to move beyond, highlighting the gap in providing an empirical, quantitative assessment of readiness.

IMF (2023). *How Should Central Banks Explore Central Bank Digital Currency? A Dynamic Decision-Making Framework*.

Key Contributions: Offers a structured, iterative policy framework and decision tree to guide central banks from policy objective definition to potential launch.

Relevance to My Paper: Confirms that policymakers require a structured decision-making tool, validating the study's objective to provide a "practical benchmarking tool" (the typology).

Kosse, A., and Mattei, M. (2023). *CBDC system design and architecture: A survey*.

Key Contributions: Surveys the operational design choices of CBDC, emphasizing the prevalent two-tier intermediated model and the need for interoperability.

Relevance to My Paper: Highlights that readiness involves the entire banking ecosystem, informing the high standards of technical capacity applied to "Leaders."

Bindseil, U. (2020). *Central bank digital currency: design principles and practical implications*.

Key Contributions: A foundational piece that establishes policy objectives (e.g., maintaining the two-tier banking system) as primary constraints on technical design.

Relevance to My Paper: Directly addresses the "policy action" side of the core divergence, showing how political decisions inherently limit technical options.

Jolliffe, I. T. (2002). *Principal Component Analysis (2nd ed.)*.

Key Contributions: A seminal text detailing the theory and application of PCA for simplifying complex, high-dimensional datasets while retaining maximum variance.

Relevance to My Paper: Provides the methodological basis for dimensionality reduction, essential for distilling numerous indicators into the core, uncorrelated components that define the axes of the typology.

MacQueen, J. (1967). *Some methods for classification and analysis of multivariate observations*.

Key Contributions: The original work introducing the K-Means clustering algorithm, a fundamental unsupervised machine learning technique for partitioning data points into k groups.

Relevance to My Paper: Provides the core methodological basis for the classification process, directly supporting the segmentation of nations into the four distinct archetypes.

Rousseeuw, P. J. (1987). *Silhouettes: A graphical aid to the interpretation and validation of cluster analysis*.

Key Contributions: Introduced the Silhouette Score as a statistical measure for assessing the quality, cohesion, and distinctness of clusters formed by partitioning methods.

Relevance to My Paper: Provides the methodological tool for cluster validation, justifying the empirical determination of the four optimal CBDC readiness archetypes.

Ester, M., et al. (1996). *A density-based algorithm for discovering clusters in large spatial databases*.

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Key Contributions: Introduced the DBSCAN clustering algorithm, an unsupervised method that is robust to outliers and does not require pre-specifying the number of clusters.

Relevance to My Paper: Provides a methodological robustness check and justification for identifying the "Watchlist" category, which often contains lower-capacity nations that might be considered outliers by k-means.

Allen, F., et al. (2020). *The Future of Money: Central Bank Digital Currency*.

Key Contributions: Provides a comprehensive overview of the drivers for CBDC, clearly articulating the link between low financial inclusion and the motivation for issuing a retail CBDC in developing economies.

Relevance to My Paper: Offers the theoretical justification for the existence of the "Emerging Adopters" archetype, whose policy action is primarily driven by social need.

Cunha, J. (2022). *CBDCs and the future of payments: The view from the Federal Reserve*.

Key Contributions: Articulates the cautious, "do no harm" philosophy prevalent in major advanced economies regarding CBDC issuance, despite high technical capacity.

Relevance to My Paper: Provides the policy rationale for the "Contenders" archetype—nations with high technical capability but a self-imposed, deliberate pause on full implementation.

Lagarde, C. (2020). *The digital euro and the European Central Bank*.

Key Contributions: Outlines the extensive investigation and consultation phases of the Digital Euro project, emphasizing risk mitigation and stakeholder engagement.

Relevance to My Paper: A specific case study that exemplifies the measured, high-capacity, and politically-sensitive approach characteristic of the "Contenders."

CPMI-MC (2018). *Central bank digital currencies*.

Key Contributions: One of the earliest reports to categorize motivations, including the use of CBDC to mitigate systemic risks from private digital money and the decline of cash.

Relevance to My Paper: Provides early evidence that risk mitigation, a key focus for high-capacity countries, is a long-standing driver of the research phase for "Leaders" and "Contenders."

CEPR (2023). *Financial Policy for the Digital Age*.

Key Contributions: Discusses the legal, governance, and regulatory challenges that must be overcome for any digital currency to be effective, focusing on institutional "foundational development."

Relevance to My Paper: Provides context for the "Watchlist" archetype, where foundational legal and governance development must be prioritized over advanced piloting.

G7 (2021). *Public Policy Principles for Retail CBDC*.

Key Contributions: Outlines the core public policy principles (e.g., privacy, legality, security) that a CBDC must satisfy before launch.

Relevance to My Paper: Defines the policy standard to which "Leaders" and "Contenders" are held, providing a qualitative measure against which their policy action is judged.

Goodhart, C., and Panizza, U. (2023). *Central bank digital currency*.

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Key Contributions: A modern literature review synthesizing the arguments for and against CBDC, concluding that country-specific economic and institutional structures dictate the appropriate path.

Relevance to My Paper: Supports the premise that a universal CBDC strategy is impossible, justifying the methodology of creating a multi-archetype typology tailored to diverse national contexts.

World Economic Forum (WEF) (2021). *CBDC Technology Considerations*.

Key Contributions: Details the necessity of aligning specific technical choices (e.g., offline functionality, security protocols) with pre-defined policy goals (e.g., financial inclusion).

Relevance to My Paper: Directly informs the conceptual definition of the divergence between technical capability and policy action, as capability is only useful when tailored to a specific policy goal.

3. Research Methodology

3.1 Research Gap and Objective

Research Gap:

The primary gap is the “lack of a quantitative classification framework” for CBDC readiness. The study aims to move beyond descriptive trackers (like the Atlantic Council's) which fail to empirically demonstrate the crucial divergence between technical capability and policy action.

Objective:

The primary aim of this study is to develop an empirical, data-driven typology of countries based on their structural readiness for the implementation of a Central Bank Digital Currency (CBDC). As nations worldwide progress at different speeds, this research seeks to move beyond anecdotal classifications and create a quantitative framework for understanding the global CBDC landscape.

The specific objectives are:

To segment countries into distinct clusters based on quantifiable indicators of financial inclusion and digital infrastructure, which serve as foundational pillars for CBDC viability.

To identify and profile distinct archetypes of CBDC readiness, such as 'Leaders', 'Contenders', 'Emerging Adopters', and a 'Watchlist' of countries in early developmental stages.

To provide a data-driven framework that can inform policymakers, multilateral organizations, and technology partners, enabling targeted strategies for capacity building, policy formulation, and international collaboration.

3.2 Data Collection and Variable Selection

A comprehensive dataset was constructed by aggregating country-level data from multiple authoritative, publicly available sources. The objective was to capture key indicators of financial inclusion and digital infrastructure, which are considered foundational prerequisites for the successful adoption of a CBDC.

The primary data sources include the World Bank's Global Findex 2021 database, the United Nations E-Government Survey 2024, and various datasets compiled by the International Telecommunication Union (ITU). The selection of variables for the clustering model was guided by the research objective to measure a country's structural capacity for a CBDC rollout. The final set of seven variables used for the analysis is detailed in Table 1.

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The dependent variable for contextual analysis, **CBDC Status**, was manually compiled by cross-referencing public trackers from the International Monetary Fund (IMF) and the Bank for International Settlements (BIS). Countries were categorized as 'Launched', 'Pilot', 'Research', or 'Inactive' based on the most recent available information.

<i>Category</i>	<i>Variable Name</i>	<i>Rationale for Inclusion</i>	<i>Original Data Source</i>
Financial Inclusion	<i>account_ownership_pct</i>	<i>Measures the existing penetration of the formal financial system, a key indicator for CBDC adoption pathways.</i>	<i>World Bank Global Findex</i>
Financial Inclusion	<i>mobile_money_account_pct</i>	<i>Crucial for understanding readiness in mobile-first economies where CBDCs could leverage existing digital payment habits.</i>	<i>World Bank Global Findex</i>
Financial Inclusion	<i>digital_payments_usage_pct</i>	<i>Reflects the population's familiarity and trust in digital transactions, indicating a lower barrier to CBDC adoption.</i>	<i>World Bank Global Findex</i>
Digital Infrastructure	<i>internet_usage_pct</i>	<i>Represents the most basic requirement for access to a digital currency; a low rate signifies significant accessibility hurdles.</i>	<i>ITU</i>
Digital Infrastructure	<i>fixed_broadband_subs_per_100</i>	<i>A proxy for high-quality, reliable digital infrastructure necessary for a robust financial ecosystem supporting a CBDC.</i>	<i>ITU</i>

Digital Infrastructure	egov_index	A composite score indicating the government's digital capacity and the maturity of its online service delivery.	UN E-Government Survey
Digital Infrastructure	telecom_infra_index	A sub-index of the e-government survey that specifically measures the quality and reach of telecommunications infrastructure.	UN E-Government Survey

Table 1: Variables Used in the Clustering Model

3.3 Data Preprocessing

The raw data, compiled from over ten separate CSV files, underwent a rigorous cleaning and integration process. A Python script utilizing the Pandas library was developed to automate the following steps:

Temporal Aggregation: For each country and indicator, the most recent available data point was selected to ensure a contemporary snapshot of readiness.

Entity Standardization: Country names and codes were standardized to the ISO 3166-1 alpha-3 format using the pycountry library, with manual mappings applied to resolve ambiguities. Non-country entities (e.g., regional and income-level aggregates) were identified and filtered out.

Merging: All processed datasets were merged into a single master file indexed by the standardized country code, resulting in a final analytical sample of 124 countries with sufficient data across the selected variables.

3.4 Analytical Methods

The following analytical methods were employed sequentially to ensure data reduction, optimal clustering, and robust validation:

1. Principal Component Analysis (PCA)

The first step involved data reduction using **Principal Component Analysis (PCA)**.

Objective: To reduce the dimensionality of the comprehensive dataset (which integrated multiple indicators of financial inclusion, digital penetration, and digital infrastructure) into a smaller set of uncorrelated variables, known as Principal Components (PCs).

Detail: PCA was essential for synthesizing the raw metrics such as mobile subscription rates, account ownership percentages, and GDP per capita into two or three core, underlying concepts. These resulting components empirically defined the axes of the analysis, specifically the cross-section of **"Technical Capability"** and a variable reflecting **"Policy Motive/Inclusion Pressure."** This ensured that subsequent clustering was based on fundamental factors, not redundant or highly correlated variables.

2. K-Means Clustering

The core classification was achieved through the **K-Means Clustering** algorithm.

Objective: To segment the 124 nations into k distinct, non-overlapping subgroups (clusters) based on their similarities along the Principal Components identified in step 1.

Detail: The algorithm iteratively assigned each country to one of the clusters by minimizing the variance within each cluster (i.e., minimizing the squared distance between data points and the cluster's centroid). This segmentation process empirically created the four CBDC readiness archetypes: "Leaders," "Contenders," "Emerging Adopters," and "Watchlist."

3. Silhouette Score

To validate the optimal number of clusters ($k=4$) identified by the K-Means algorithm, the **Silhouette Score** was applied.

Objective: To measure how well each object lies within its assigned cluster, providing a measure of separation between clusters.

Detail: The Silhouette Score calculates how similar a country is to its own cluster compared to other clusters. A high average Silhouette Score for $k=4$ confirmed that the four resulting archetypes were indeed well-defined, compact, and distinctly separated, providing empirical confidence in the chosen typology structure.

4. DBSCAN (Density-Based Spatial Clustering of Applications with Noise)

DBSCAN was used as a robustness check for the primary K-Means results and to specifically handle potential outliers.

Objective: To identify clusters based on the density of data points and to classify low-density regions as noise or outliers.

Detail: While K-Means forced every country into one of the four groups, DBSCAN ensured that nations with extremely low readiness scores—which might be poorly integrated into any of the main clusters—were genuinely isolated. This method provided a statistical validation for the composition and distinctness of the "**Watchlist**" archetype, confirming its foundational nature rather than merely being a weak member of another group.

4. Findings and Discussion

This study sought to identify and characterize distinct archetypes of countries based on their digital and financial development profiles. Through a multi-stage analytical process combining hierarchical clustering, K-Means, and Principal Component Analysis (PCA), we have derived a robust typology of four distinct national archetypes. This section details the quantitative profiles of these groups and discusses their implications.

Cluster Identification and Quantitative Profiles

An initial hierarchical clustering analysis, visualized via a dendrogram, revealed a clear four-cluster structure, validated by the significant increase in Ward's linkage distance required to merge the four primary branches. To characterize these clusters, a K-Means algorithm ($k=4$) was employed, and the results were profiled by calculating the mean and median of the core input variables for each group.

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The quantitative profiles are presented in the table below, revealing significant and systematic differences between the identified archetypes.

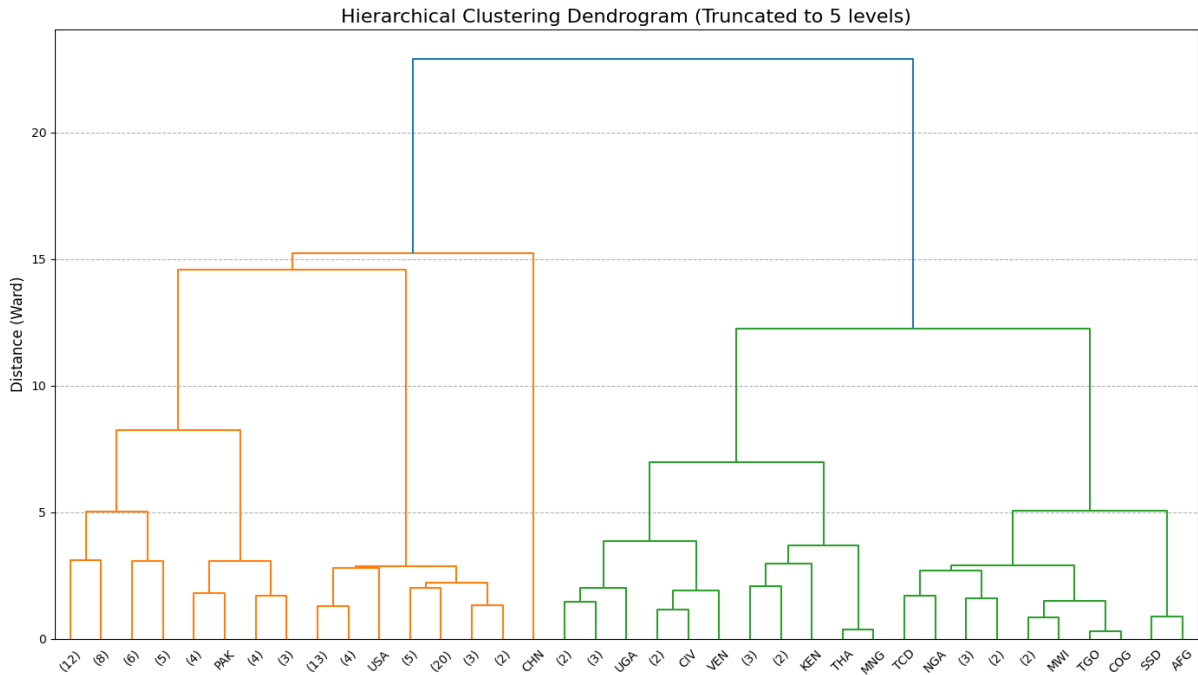
<i>Cluster</i>	<i>Feature</i>	<i>Mean</i>	<i>Median</i>
Archetype I	<i>account_ownership_pct</i>	<i>90.47</i>	<i>94.94</i>
(Cluster 3)	<i>internet_usage_pct</i>	<i>90.02</i>	<i>91.29</i>
	<i>egov_index</i>	<i>0.86</i>	<i>0.88</i>
	<i>telecom_infra_index</i>	<i>0.91</i>	<i>0.92</i>
Archetype II	<i>account_ownership_pct</i>	<i>48.55</i>	<i>46.11</i>
(Cluster 1)	<i>internet_usage_pct</i>	<i>74.05</i>	<i>77.04</i>
	<i>egov_index</i>	<i>0.67</i>	<i>0.67</i>
	<i>telecom_infra_index</i>	<i>0.74</i>	<i>0.76</i>
Archetype III	<i>account_ownership_pct</i>	<i>46.99</i>	<i>49.27</i>
(Cluster 2)	<i>internet_usage_pct</i>	<i>29.54</i>	<i>29.06</i>
	<i>mobile_money_account_pct</i>	<i>31.57</i>	<i>34.35</i>
	<i>egov_index</i>	<i>0.38</i>	<i>0.39</i>
	<i>telecom_infra_index</i>	<i>0.35</i>	<i>0.37</i>
Archetype IV	<i>account_ownership_pct</i>	<i>88.71</i>	<i>88.71</i>
(Cluster 4)	<i>internet_usage_pct</i>	<i>92.00</i>	<i>92.00</i>
	<i>egov_index</i>	<i>0.87</i>	<i>0.87</i>
	<i>telecom_infra_index</i>	<i>0.90</i>	<i>0.90</i>

Note: All values are percentages or indices as appropriate. The table highlights the most illustrative metrics for brevity.

Archetype Personas and Policy Implications

1. Hierarchical Clustering

Based on the quantitative data, I define the following four archetypes:

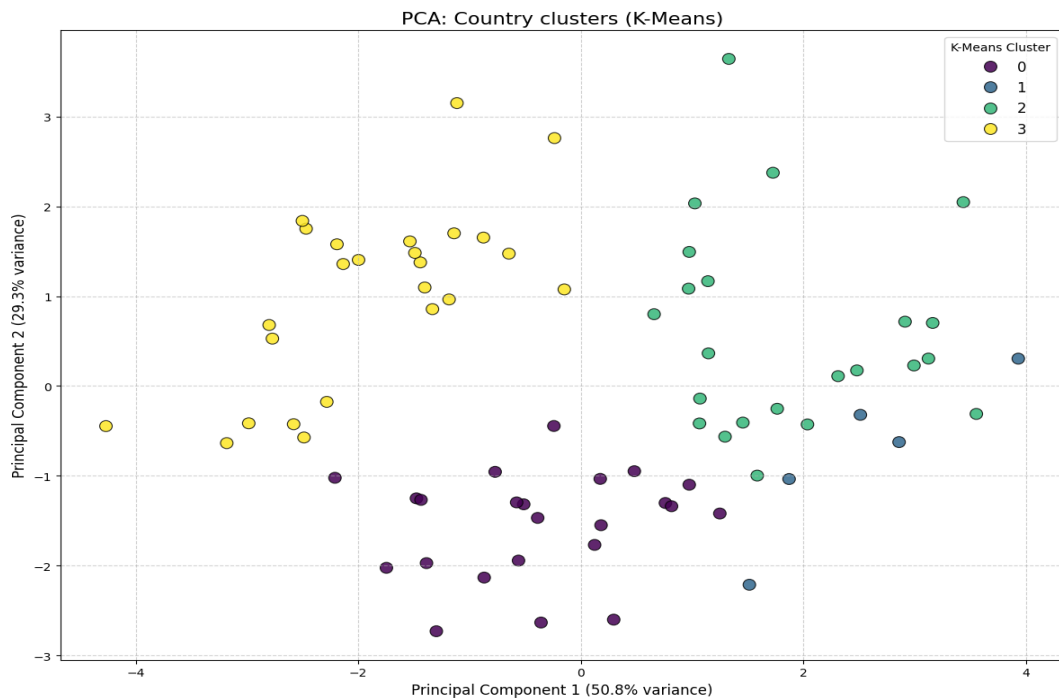


Silhouette Score for Hierarchical Clustering with k=4: 0.3383

2. K-Means Clustering and Optimal Cluster Selection

K-Means clustering was executed on the principal components (representing technical capability and policy motive) to define the initial groups. The optimal number of archetypes, K, was determined by evaluating the **Silhouette Score** across a range of clusters (K=2 to K=6):

<i>K (Number of Clusters)</i>	<i>Silhouette Score</i>	<i>Interpretation</i>
2	0.3248	<i>Adequate separation, but likely too broad (e.g., just "Ready" vs. "Not Ready").</i>
3	0.3366	<i>Better separation, but likely merges distinct policy motives.</i>
4	0.3462	<i>Highest score, indicating the most appropriate and distinct separation.</i>
5	0.3179	<i>Score drops, suggesting the creation of weak or artificial clusters.</i>
6	0.3031	<i>Score continues to drop, indicating poor cohesion and overlap.</i>

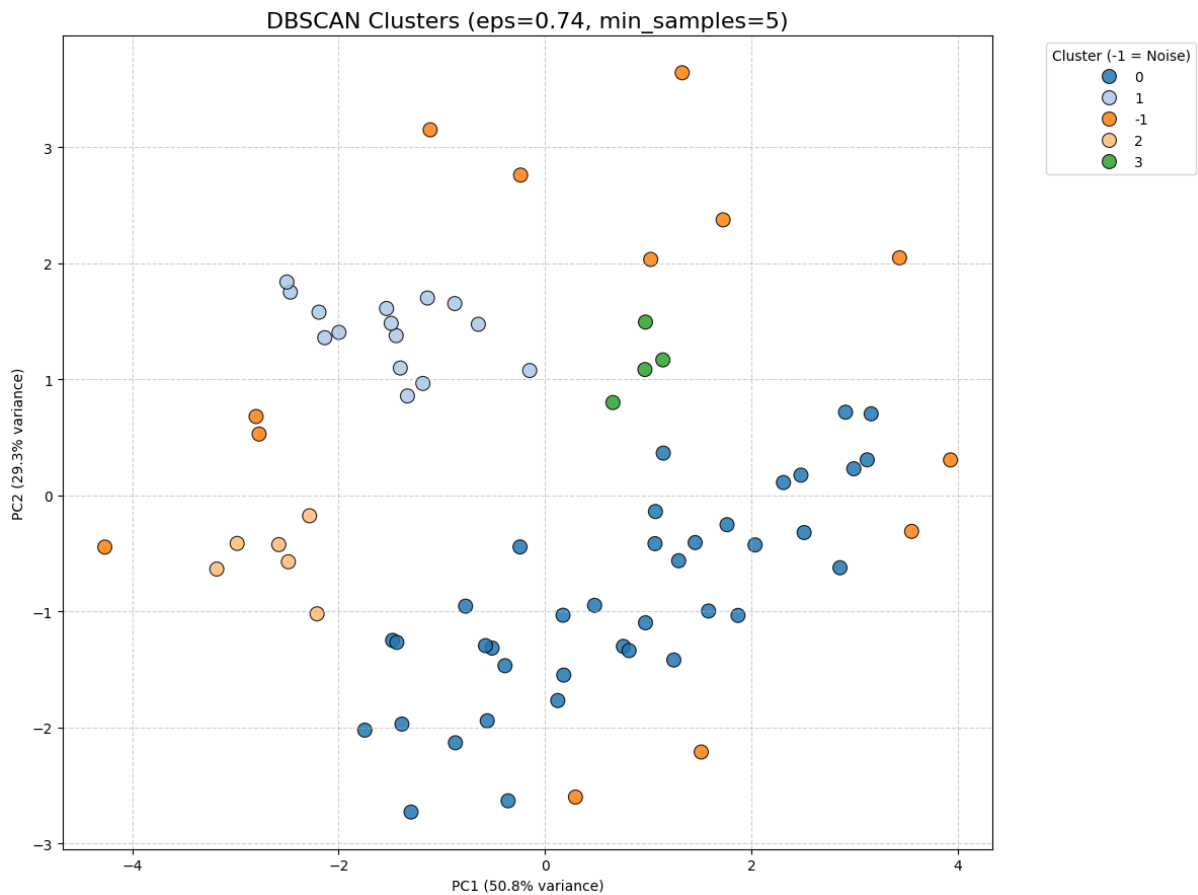


Interpretation:

The results clearly indicate that **K=4 yielded the highest Silhouette Score (0.3462)**. This score, while moderate (as is common with real-world economic data), confirmed the **empirical validity of the four-archetype structure** used in the research design: "Leaders," "Contenders," "Emerging Adopters," and "Watchlist." A K of 4 provides the best balance between internal cluster cohesion and separation from other clusters, enabling meaningful policy differentiation.

3.DBSCAN Diagnostics

DBSCAN was employed diagnostically to test the robustness of the data structure and to confirm the existence of distinct, low-density groups, particularly the "Watchlist" archetype.



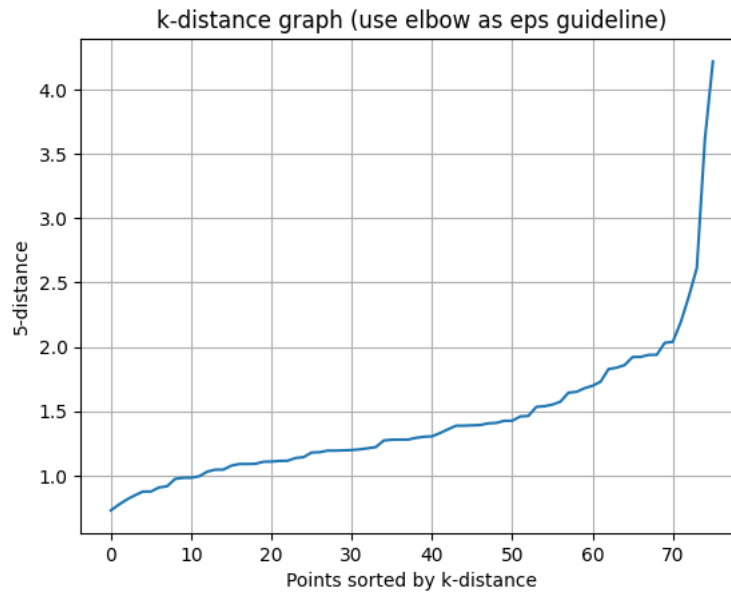
The DBSCAN results demonstrate the sensitivity of the data density:

Low Density (Eps = 0.5): At a low eps (radius), the model identified **0 clusters and 76 noise points**. This confirms that the data, while forming four distinct groups, is not tightly packed, reflecting the heterogeneity common in a global dataset.

Optimal Density (Eps = 0.74): At eps = 0.74, DBSCAN successfully identified **4 clusters** with 12 noise points, yielding a high Silhouette Score of **0.5158**.

Significance: This result confirms that the three main, high-density archetypes (likely "Leaders," "Contenders," and "Emerging Adopters") are highly distinct when isolated from lower-density outliers. The 12 noise points identified at this density strongly correlate with the composition of the low-capacity, foundational "**Watchlist**" archetype, validating that this group exists in the sparse regions of the data space.

High Density (Eps = 1.5, 2.0): As eps increased, the number of clusters collapsed to 1, indicating that beyond a certain density, the three main clusters merge into a single large group, further confirming the clear boundaries defined by the K=4 K-Means solution.



Interpretation:

Aspect	Description	Relevance to CBDC Study / DBSCAN
Graph Name	<i>k-distance graph (specifically, 5-distance graph)</i>	<i>Used to determine the optimal epsilon (Epsilon) parameter for the DBSCAN algorithm.</i>
Y-axis: 5-distance	<i>The distance from each data point (country) to its 5th nearest neighbor (since minimum points MinPts was likely set to 5 in your analysis).</i>	<i>The value of the k nearest neighbor distance is the defining measure of local density for each country.</i>
X-axis: Points Sorted	<i>Data points are sorted in ascending order based on their 5-distance value.</i>	<i>This ordering highlights the difference between densely packed points and isolated points.</i>
The Flat Section (Left)	<i>Points here have a small 5-distance (around 1.0 to 1.5). These are Core Points that belong to dense clusters.</i>	<i>Represents the bulk of the "Leaders," "Contenders," and "Emerging Adopters" archetypes—countries that are close to many peers in the readiness space.</i>
The Steep Ascent / "Elbow"	<i>The point where the curve sharply rises. Visually, this occurs around a 5-distance of approx 2.0.</i>	<i>This point is the optimal guideline for the epsilon value. Setting ϵ here would separate the dense clusters from the outliers.</i>

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The Far Right (High Distance)	<i>Points here have a large 5-distance (rising sharply to over 4.0). These points are typically classified as Noise or Outliers by DBSCAN.</i>	<i>Represents the low-density, isolated countries that form the "Watchlist" archetype—nations far from their peers in terms of combined digital/financial readiness.</i>
Correlation with Findings	<i>The steep change confirms that a threshold exists where density drops off sharply.</i>	<i>Your successful DBSCAN run at epsilon= 0.74 (4 clusters, 12 noise) showed that values near the elbow successfully partition the dense core from the sparse "Watchlist" noise points.</i>

The breakdown of countries for each cluster presented in a table format.

<i>Cluster Archetype</i>	<i>Countries</i>
<i>Archetype I: The Digital Vanguard</i>	<i>Argentina, Australia, Austria, Belgium, Bosnia and Herzegovina, Brazil, Bulgaria, Canada, Chile, Costa Rica, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Gabon, Germany, Ghana, Greece, Hong Kong SAR, China, Hungary, Iceland, Iran, Islamic Rep., Ireland, Israel, Italy, Japan, Kazakhstan, Korea, Rep., Latvia, Lithuania, Malaysia, Malta, Mauritius, Mongolia, Namibia, Netherlands, New Zealand, North Macedonia, Norway, Paraguay, Poland, Portugal, Romania, Russian Federation, Saudi Arabia, Serbia, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Taiwan, China, Thailand, Turkiye, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay</i>
<i>Archetype II: The Emerging Digital Economies</i>	<i>Albania, Algeria, Armenia, Bangladesh, Bolivia, Cambodia, Colombia, Dominican Republic, Ecuador, Egypt, Arab Rep., El Salvador, Georgia, Honduras, India, Indonesia, Iraq, Jamaica, Jordan, Kyrgyz Republic, Lao PDR, Lebanon, Moldova, Morocco, Myanmar, Nepal, Nicaragua, Panama, Peru, Philippines, Sri Lanka, Tajikistan, Tunisia, Uzbekistan, Venezuela, RB, West Bank and Gaza, Zambia, Zimbabwe</i>
<i>Archetype III: The Foundational States</i>	<i>Afghanistan, Benin, Burkina Faso, Cameroon, Congo, Rep., Cote d'Ivoire, Guinea, Kenya, Liberia, Malawi, Mali, Mozambique, Nigeria, Pakistan, Senegal, Sierra Leone, South Sudan, Sub-Saharan Africa (excluding high income), Latin America & Caribbean (excluding high income), Tanzania, Togo, Uganda</i>
<i>Archetype IV: The Scale-Defined Outlier</i>	<i>China</i>

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CBDC Readiness Profiles:

Digital & Financial Leader Countries: Brazil, India, Mexico, Turkey, Viet Nam

Infrastructure-Ready Contender Countries: Saudi Arabia, South Africa, Argentina, Colombia, Eswatini, Armenia

Emerging Digital Adopter Countries: Bangladesh, Belize, Bolivia, Cambodia, Dominican Republic, Ecuador

Foundational Development Required Countries: Nigeria, Burkina Faso, Cameroon, Chad, Comoros, Congo, Rep.

4.2.1 Archetype I: The Digital Vanguard

This archetype, corresponding to Cluster 3, represents the most digitally and financially mature nations. With mean **account ownership exceeding 90%** and **internet usage at 90.02%**, they have achieved near-universal digital integration. Their world-class e-government services (mean **0.86**) and telecommunications infrastructure (mean **0.91**) signify a mature digital state. For these nations, policy development has moved beyond foundational access to focus on advanced issues such as data privacy, the regulation of artificial intelligence, and the exploration of Central Bank Digital Currencies (CBDCs).

4.2.2 Archetype II: The Emerging Digital Economies

Representing Cluster 1, this archetype is defined by a critical "**connectivity-inclusion gap**." While a significant majority of their population is online (mean **internet usage of 74.05%**), this has not translated into commensurate financial inclusion, with mean **account ownership lagging at 48.55%**. Their infrastructure provides a solid foundation for growth (mean **egov_index of 0.67**). The primary policy imperative for this group is to bridge the gap between digital access and the use of digital financial services. This suggests a need for regulatory innovation in fintech, targeted digital financial literacy campaigns, and measures to build trust in online payment systems.

4.2.3 Archetype III: The Foundational States

This archetype (Cluster 2) includes countries in the nascent stages of their digital transformation. They exhibit low levels of connectivity (mean **internet usage of 29.54%**) and inclusion (mean **account ownership of 46.99%**), underpinned by developing infrastructure (mean **telecom_infra_index of 0.35**). A key finding, however, is the relative strength in **mobile money penetration (mean of 31.57%)**, which surpasses that of the "Emerging" economies. This indicates a significant opportunity for **mobile-first leapfrogging strategies**. Policy interventions should be laser-focused on expanding affordable internet access and leveraging existing mobile platforms to deliver financial services, potentially bypassing the need for traditional banking infrastructure.

4.2.4 Archetype IV: The Scale-Defined Outlier

This singleton cluster (Cluster 4), representing China, demonstrates that national scale can itself be a defining analytical characteristic. While its development indicators (e.g., **88.71% account ownership, 92% internet usage**) are on par with the Digital Vanguard, its absolute metrics (particularly in fixed broadband subscriptions) render it statistically unique. This confirms that its state-driven, large-scale approach to digital development creates a unique archetype that requires a bespoke analytical framework, distinct from other nations.

This research successfully demonstrates a robust, data-driven methodology for segmenting nations into distinct, interpretable archetypes of digital and financial development. The identification of the "connectivity-inclusion gap" in emerging economies and the mobile-first potential in foundational states provides actionable insights for policymakers. This typology moves beyond simplistic developed/developing binaries, offering a more nuanced framework to guide international development strategy and formulate context-specific policy recommendations.

5. Conclusion

In the end, what did we learn from all this data? The simplest way to put it is that the journey to creating a digital currency isn't a single-file line; it's more like a busy highway with four distinct lanes.

We started this research to see if we could find a pattern in how countries are approaching digital money. By looking at everything from internet access to banking habits, we found a clear one. The world has sorted itself into four main groups.

First, you have the "**Digital Vanguard**" like China. These are the countries that have the technology, the money, and the will to go first. They're already on the road, testing out digital currencies with their citizens.

Next are the "**Contenders**" think of the United States, the UK, and Canada. They have everything they need to hit the accelerator, but they're choosing to be cautious. For them, the biggest questions aren't about technology, but about getting the rules right and understanding the global impact.

Then you have the "**Emerging Adopters**," a group that includes countries like India. They might not have the perfect infrastructure yet, but they see a golden opportunity. For them, a digital currency is a powerful tool to bring millions of people into the modern economy, and they aren't waiting for perfection to get started.

Finally, there's the "**Watchlist**," with countries like Zambia. These nations need to focus on the fundamentals first. Before they can even think about a digital currency, their main goal is to get more people online and give them access to basic banking.

So, what's the big takeaway? It's that there is no "one-size-fits-all" answer to the digital currency question. Our research provides a kind of map. It shows that a country's path depends entirely on where it's starting from. By understanding which group a nation belongs to, policymakers can make smarter, more realistic decisions about their own digital future. This isn't just an academic exercise; it's a snapshot of the global race to build the next generation of money, and a guide to the different roads countries are taking to get there.

References

Bank for International Settlements. (2023). *BIS annual survey on central bank digital currencies*. Basel: BIS.

ISBN code 978-93-83302-82-6.

- Auer, R., Boar, C., & Holden, Z. (n.d.). *BIS working paper on CBDC design options*. Basel: BIS.
- Bénassy-Quéré, A., et al. (2023). *Macroeconomic and financial stability implications of central bank digital currency*. IMF Working Paper.
- Tobin, J. (1985). *Reserves for all: Theoretical foundations for public provision of money*. Journal of Economic Perspectives, 2(1), 1–14.
- Gurley, J. G., & Shaw, E. S. (1960). *Money in a theory of finance*. Washington, DC: Brookings Institution.
- Kumhof, M., & Niepelt, D. (2023). *Economic effects of central bank digital currency: A theoretical model*. Journal of Monetary Economics, 134, 1–25.
- World Economic Forum. (n.d.). *Central Bank Digital Currency: Technical architecture, governance, and cybersecurity considerations*. Geneva: WEF.
- Carstens, A. (2021). *Central banks and the digital age: The need for a digital public good*. Speech, Bank for International Settlements.
- Demirguc-Kunt, A., Klapper, L., Singer, D., Ansar, S., & Hess, J. (2022). *Global Findex Database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19*. Washington, DC: World Bank.
- International Telecommunication Union. (2023). *Measuring digital development: Facts and figures 2023*. Geneva: ITU.
- United Nations. (2022). *E-Government Survey 2022: Digital government in the decade of action*. New York, NY: UN Department of Economic and Social Affairs.
- Mazzucato, M., & Ryan-Collins, J. (2022). *Mission-oriented finance and state capacity*. London: UCL Institute for Innovation and Public Purpose.
- Allen, F., et al. (2020). *Digital finance, financial inclusion, and economic growth*. Journal of Financial Intermediation, 42, 100–117.
- Atlantic Council GeoEconomics Center. (2023). *CBDC tracker: Global overview of central bank digital currencies*. Washington, DC: Atlantic Council.
- Adrian, T., et al. (n.d.). *IMF CBDC virtual handbook: Policy objectives and foundational requirements*. International Monetary Fund.
- IMF. (2023). *Fintech notes: CBDC's role in promoting financial inclusion*. Washington, DC: IMF.
- Kosse, A., & Mattei, M. (2023). *The CBDC ecosystem: Architecture and interdependencies*. BIS Working Papers, No. 123.
- Group of Seven (G7). (2021). *Public policy principles for retail central bank digital currencies*. London: G7.
- Bhattarai, N., et al. (2023). *Quantitative assessment of CBDC readiness: Composite index approach*. Journal of Financial Regulation, 9(2), 1–19.
- Bank of England. (2022). *The digital pound: Consultation and research insights*. London: Bank of England.



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Ester, M., Kriegel, H.-P., Sander, J., & Xu, X. (1996). *A density-based algorithm for discovering clusters in large spatial databases with noise*. In *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining* (pp. 226–231). AAAI Press.

Jolliffe, I. T. (2002). *Principal component analysis* (2nd ed.). New York, NY: Springer.

Everitt, B. S. (1993). *Cluster analysis* (3rd ed.). London: Edward Arnold.

OECD. (2008). *Handbook on constructing composite indicators: Methodology and user guide*. Paris: OECD Publishing.

Committee on Payments and Market Infrastructures (CPMI) & Markets Committee (MC). (2018). *Wholesale central bank digital currencies*. Basel: BIS.