“Factors linking upper-middle- and high-income countries in terms of banking ecosystem digitalization: Cluster analysis”

AUTHORS	Sevinj Abbasova Tetiana Vasylieva R Mehriban Aliyeva Aybaniz Gubadova Nigar Ashurbayli-Huseynova Lala Kasumova

ARTICLE INFO	Sevinj Abbasova, Tetiana Vasylieva, Mehriban Aliyeva, Aybaniz Gubadova, Nigar Ashurbayli-Huseynova and Lala Kasumova (2025). Factors linking upper-middle- and high-income countries in terms of banking ecosystem digitalization: Cluster analysis. *Banks and Bank Systems*, *20*(3), 75-90. doi:10.21511/bbs.20(3).2025.06
DOI	http://dx.doi.org/10.21511/bbs.20(3).2025.06
RELEASED ON	Friday, 19 September 2025
RECEIVED ON	Thursday, 07 August 2025
ACCEPTED ON	Wednesday, 10 September 2025
LICENSE	This work is licensed under a Creative Commons Attribution 4.0 International License
JOURNAL	"Banks and Bank Systems"
ISSN PRINT	1816-7403
ISSN ONLINE	1991-7074
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
54	1	12

© The author(s) 2025. This publication is an open access article.

BUSINESS PERSPECTIVES

LLC “CPC “Business Perspectives”
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Sevinj Abbasova (Azerbaijan), **Tetiana Vasylieva** (Germany),
Mehriban Aliyeva (Azerbaijan), **Aybaniz Gubadova** (Azerbaijan),
Nigar Ashurbayli-Huseynova (Azerbaijan), **Lala Kasumova** (Azerbaijan)

FACTORS LINKING UPPER-MIDDLE- AND HIGH-INCOME COUNTRIES IN TERMS OF BANKING ECOSYSTEM DIGITALIZATION: CLUSTER ANALYSIS

Type of the article: Research Article

Received on: 7th of August, 2025
Accepted on: 10th of September, 2025
Published on: 19th of September, 2025

© Sevinj Abbasova, Tetiana Vasylieva, Mehriban Aliyeva, Aybaniz Gubadova, Nigar Ashurbayli-Huseynova, Lala Kasumova, 2025

Sevinj Abbasova, Ph.D., Associate Professor, Head of Department of Applied Economics, Azerbaijan State University of Economics (UNEC), Azerbaijan.

Tetiana Vasylieva, DSc., Professor, Technische Universität Bergakademie Freiberg [Technical University Freiberg Mining Academy], Germany.

Mehriban Aliyeva, Ph.D., Associate Professor, Department of Applied Economics, Azerbaijan State University of Economics (UNEC), Azerbaijan. (Corresponding author)

Aybaniz Gubadova, Ph.D., Associate Professor, Department of Applied Economics, Azerbaijan State University of Economics (UNEC), Azerbaijan.

Nigar Ashurbayli-Huseynova, Ph.D., Associate Professor, Department of Applied Economics, Azerbaijan State University of Economics (UNEC), Azerbaijan.

Lala Kasumova, Ph.D., Senior Lecturer, Department of Applied Economics, Azerbaijan State University of Economics (UNEC), Azerbaijan.

This is an Open Access article, distributed under the terms of the Creative Commons Attribution 4.0 International license, which permits unrestricted re-use, distribution, and reproduction in any medium, provided the original work is properly cited.

Conflict of interest statement:
Author(s) reported no conflict of interest

Abstract

The banking and financial system of the countries of the world is constantly developing, but at different rates and ways, given their differences in the levels of economic, financial, and innovation development. The purpose of this article is to identify factors that link upper-middle- and high-income countries in terms of banking ecosystem digitalization, based on cluster analysis. The research sample includes 40 countries – 20 top-performing upper-middle-income and 20 high-income economies – based on the 2023 ICT Development Index. The analysis is based on 15 standardized indicators characterizing digitalization in the banking ecosystem, sourced from the International Monetary Fund, the World Bank, and the International Telecommunication Union. These indicators cover ICT development, AI readiness, cybersecurity, GovTech maturity, financial development, banking access, and digital transaction activity. Data standardization was performed in Stata (v19.5) using the built-in function to create new variables with a mean of 0 and a standard deviation of 1. Cluster analysis was conducted using the k-means method in Statgraphics (v19), with silhouette scores computed in Python to determine the optimal number of clusters. Cluster analysis revealed four distinct country groups, demonstrating that similarities in banking ecosystem digitalization transcend income levels. Key convergence factors include ICT development, GovTech maturity, mobile banking adoption, and AI readiness. Some upper-middle-income countries exhibit digitalization patterns comparable to high-income economies, highlighting the role of strategic investment and policy, rather than income, as primary drivers of digital financial advancement.

Keywords AI, ATM, e-banking, FinTech, GovTech, ICT, Internet, mobile banking, security, transaction

JEL Classification G21, O33, C38

INTRODUCTION

In recent years, the rapid advancement of digital technologies has significantly transformed global financial systems, giving rise to what is increasingly referred to as the digital banking ecosystem. This transformation is not only altering the traditional structure and operations of financial institutions but is also reshaping the economic development strategies of both advanced and emerging economies. The integration of information and communication technologies (ICT), artificial intelligence (AI), and digital financial services has become a cornerstone of modern economic competitiveness and financial inclusion.

Traditionally, countries have been classified and analyzed based on income groups as defined by international organizations such as the World Bank. However, recent global developments suggest that this classification alone cannot explain a country’s level of technological advancement or the maturity of its banking ecosystem. Some upper-middle-income countries have made substantial progress in digital banking infrastructure and service adoption, in some cases outperforming lower-ranked high-income countries (Financial Development Index, ICT Development Index, AI Preparedness Index, Global Cybersecurity Index, GovTech Maturity Index, etc.). This phenomenon calls for a more nuanced analysis of the factors that influence digital transformation in banking, beyond income-based categorizations.

The digitalization of banking ecosystems encompasses a broad range of indicators, including the development of ICT infrastructure, AI readiness, cybersecurity capabilities, digital public services, and the penetration of digital financial products such as mobile payments, online banking, and card usage. These components collectively define the readiness and functionality of a country's banking ecosystem in a digital age. As such, a multidimensional analysis is necessary to assess and compare countries' performance in this area.

Therefore, it is a relevant issue to explore the extent to which countries from different income groups exhibit similarities in digital banking development, and what structural or policy-related factors contribute to their clustering.

1. LITERATURE REVIEW

The digitalization of banking ecosystems represents a global phenomenon driven by advances in financial technology (fintech), cybersecurity, regulatory innovation, and customer-centric platforms.

Digital banking adoption is influenced by customer perceptions and technology readiness. Kadri (2025) identifies key determinants of e-banking adoption, such as perceived trust, ease of use, and digital literacy, especially in commercial banks. In China, DingYi et al. (2024) explore how state support, consumer trust, and the strategic role of citizen banking are central to digital banking success. These foundational works underline the necessity for both infrastructure and trust in driving user adoption. From a business perspective, Berisha and Rayfield (2025) demonstrate that internal fintech significantly boosts bank profitability, while Ivashchenko et al. (2018) emphasize the role of fintech platforms in improving SME access to finance, drawing from the EU's experience. Wang et al. (2024) and Zhou (2024) further elaborate that digital transformation supports corporate social responsibility and enhances financial performance, fostering long-term sustainability. Murshudli (2018) and Murshudli and Loguinov (2019, 2020) determined that digitalization helps international banks achieve competitive advantages, creates favorable conditions for innovation, significantly increases the efficiency of international banking operations, and accelerates the growth of global financial capital flows.

Smart technologies are reshaping the operational landscape of banks. Hrytsenko et al. (2024) discuss the integration of smart systems, AI, and data analytics, linking these to enhanced decision-making and fraud detection. Kuzior et al. (2022b) analyze digital convergence on a global scale, focusing on cybersecurity, business transparency, and AML mechanisms. Innovation is also redefining systemic frameworks. Shafranova et al. (2024) provide a comparative analysis of central bank digital currency versus the quantum financial system, while Holtfort and Horsch (2024) offer a broader literature review on quantum economics, suggesting that these innovations may redefine monetary structures and banking intermediation.

Cybersecurity remains a critical concern across digital financial ecosystems. Dobrovolska and Rozhkova (2024) investigate how digitalization supports anti-corruption efforts and enhances cyber-fraud defenses. Supporting this, Dobrovolska et al. (2024) examine the interconnection between health security and cybersecurity. Lyeonov et al. (2024) draw attention to heightened financial fraud during wartime, stressing the need for adaptive digital protection mechanisms in unstable environments. The strategic role of information openness is emphasized by Lyeonov et al. (2023),

http://dx.doi.org/10.21511/bbs.20(3).2025.06

who argue that transparency in the digital environment enhances business leadership. This aligns with Kuzior et al. (2022a), reinforcing that digital transformation is not solely technological but also institutional and cultural, driven by openness and accountability.

In the last decade, a direction of digital banking, known as Open Banking, has been actively developing. This statement is confirmed by numerous scientific papers on the subject under study. In academic circles, the issues of formation and development of the Open Banking system are discussed at international conferences, congresses, webinars, and are disclosed in articles (Mourshoudli et al., 2020). Several studies link digital banking to broader goals of financial inclusion. Maatallah (2024) explores the socio-economic challenges of digital transformation in marginalized communities, while Dluhopolskyi et al. (2023) highlight COVID-19's role in accelerating digital financial inclusion. Huseynov et al. (2025) provide critical insights into Azerbaijan's digital economy, identifying infrastructure, education, and investment gaps as barriers. Mursalov et al. (2023) analyze the synergy between entrepreneurial ecosystems and digitalization, advocating for regional development strategies to support innovation clusters.

The success of digital banking also depends on human capital and internal capabilities. Annisa et al. (2024) emphasize that employee self-efficacy significantly mediates the impact of digital transformation on performance. Al Afaishat et al. (2024) and Abou-Moghli (2025) find that organizational alignment and resource availability shape the outcomes of digital strategies, particularly in the financial and insurance sectors. Al-Smadi (2025) and Dillianti et al. (2024) extend this analysis to the insurance sector, showing that digital innovation leads to measurable performance improvements when readiness is high. These insights are crucial for ecosystem mapping, as sectoral readiness influences the clustering and scalability of digital transformation.

Banking digitalization is not isolated but closely tied to broader economic systems. Kuzior et al. (2024) model the influence of digital economies on broader economic outcomes, while Dobrovolska and Kolomiiets (2024) explore the effect of digitalization on the social determinants. These studies reflect the ecosystemic nature of digital transformation. Polishchuk (2023) expands on the synergy between entrepreneurial ecosystems and digitalization, suggesting that ecosystem thinking is essential for fostering innovation.

New fintech paradigms are emerging at the intersection of technology, governance, and education. Ali Mustafa (2024) proposes integrating financial literacy, RegTech, and DeFi to create a resilient digital finance framework. Okoli (2024) offers a regional view from Africa, noting the nonlinear relationship between fintech adoption and banking stability. Minh Sang (2024) provides bibliometric insights into digital marketing trends, reflecting the growing importance of digital presence and customer analytics. Krawczyk et al. (2025) propose a benchmarking model that could support cluster-based evaluation of digital banking resilience across nations.

This review creates a foundation for cluster analysis by identifying key thematic areas, institutional dynamics, and regional contrasts in digital banking development.

The purpose of the article is to justify factors of linking upper-middle- and high-income countries in terms of banking ecosystem digitalization based on cluster analysis.

2. METHODS

The research sample consists of 40 world countries, including the top 20 countries in the ICT Development Index (IDI) within the upper-middle income group (Armenia and the Russian Federation were excluded from the sample due to the authors' beliefs) and the top 20 countries in IDI rating within high-income economies (Appendix A). The World Bank Income group is dated July 2023, as IDI is dated 2023 too (ITU, n.d.).

The information base is statistical data provided by the International Monetary Fund, the World Bank, and the International Telecommunication Union within 15 investigated indicators (i1–i15) that are given below and characterize the level of countries' banking ecosystem digitalization:

- I1 – ICT Development Index overall score (IDI) (ITU, n.d.);

- I2 – AI Preparedness Index overall score (AIPI) (IMF, n.d.a);
- I3 – Global Cybersecurity Index overall score (GCI) (World Bank, n.d.b);
- I4 – GovTech Maturity Index (GTMI) (World Bank, n.d.c);
- I5 – Financial Development Index (FDI) (IMF, n.d.c);
- I6 – Digital Data Use Indicator (World Bank, n.d.a);
- I7 – Using Mobile Phone / the Internet for online purchase (World Bank, n.d.h);
- I8 – Using Mobile Phone / the Internet to Pay Bills (World Bank, n.d.i);
- I9 – Using Financial Services – Deposit Accounts (World Bank, n.d.f);
- I10 – Using Financial Services – Loan accounts (World Bank, n.d.g);
- I11– Using Financial Services – Debit cards (World Bank, n.d.e);
- I12 – Using Financial Services – Credit cards (World Bank, n.d.d);
- I13 – Number of automated teller machines (ATMs) (IMF, n.d.b);
- I14 –Number of mobile and internet banking transactions (IMF, n.d.b);
- I15 –Value of mobile and internet banking transactions (% of GDP) (IMF, n.d.b).

All the above indicators have different units of measurement, so it is necessary to pre-standardize the data to improve the quality of the research. To create new standardized variables, the 'egen' command with the std () function is used in StataNow SE 19.5 software (Appendix A). This command will create a new variable with a mean of 0 and a standard deviation of 1:

$$egen\ std\_variable = std\ \left(original\_variable\right). \tag{1}$$

For cluster analysis, the k-means method is applied. K-means is a machine learning algorithm used to partition a dataset into k distinct, non-overlapping clusters based on feature similarity. It aims to minimize the within-cluster variance (i.e., the sum of squared distances between each point and its cluster center) (Jain et al., 1999; Ahmed et al., 2020). Firstly, k is chosen (the number of clusters), and k centroids are randomly initialized. Secondly, each data point is assigned to the nearest centroid, and then there is a recalculation of the centroids as the mean of the assigned points. Steps are repeated until convergence (centroids no longer change significantly) (Appendix B). This method works well for large numbers of observations and variables, especially with standardized data, and provides direct cluster membership and centroids, which are interpretable. The limitation is the requirement to predefine k (number of clusters) (Appendix B).

K-means method is conducted using Statgraphics 19 software (Polhemus, n.d.). Python is used to compute the silhouette scores to ground the number of clusters (Statgraphics, n.d.).

3. RESULTS AND DISCUSSION

To justify factors of linking upper-middle- and high-income countries in terms of banking ecosystem digitalization, the cluster analysis is applied based on the above method and software.

K-means clustering for each k from 2 to 8 is performed in Appendix B (Tables B1 to B7). Table 1 shows the final cluster size summary (k = 2 to 8).

Table 1. Cluster size summary (k = 2 to 8)

k	Cluster Sizes	Smallest Cluster (%)	Notes
2	19, 21	–	Balanced
3	19, 3, 18	7.5%	Small cluster
4	10, 3, 17, 10	7.5%	Still imbalanced
5	9, 3, 14, 7, 7	7.5%	Fragmented
6	7, 3, 14, 7, 7, 2	5%	Highly fragmented
7	4, 4, 14, 6, 7, 2, 3	5%, 7.5%	3 clusters < 5 obs
8	3, 4, 14, 6, 7, 2, 3, 1	2.5%, 3 clusters < 5 obs	Worst fragmentation

http://dx.doi.org/10.21511/bbs.20(3).2025.06

Overclustering clearly begins around k > 4; k = 6 to 8 leads to many small or outlier clusters. Cluster 6, 7, or 8 often captures only 1-3 observations. These do not reflect strong or reliable segments – likely outliers. Best balance seems at: k = 2 (simple, clean, balanced), k = 3 (adds nuance but still one small cluster), k = 4 (adds another layer but retains one weak cluster). Therefore, it is necessary to confirm the optimal number of clusters statistically with the silhouette scores for each k (Table 2).

Table 2. Silhouette scores for each number of clusters (k from 2 to 8)

k	Silhouette Score
2	0.240
3	0.265
4	**0.267**
5	0.175
6	0.219
7	0.166
8	0.157

The optimal number of clusters is likely k = 4, since it gives the highest silhouette score. After k = 4, the score drops noticeably, which indicates overfragmentation. Though k = 3 is close in value, k = 4 likely offers better separation and cohesion.

Table 3 presents the membership table.

Table 3. Cluster analysis results (countries' membership table)

Row	Country	Cluster	Row	Country	Cluster
1	Albania	1	21	Kuwait	1
2	Argentina	1	22	Latvia	3
3	Australia	3	23	Libya	1
4	Azerbaijan	4	24	Malaysia	3
5	Bahrain	4	25	Mauritius	4
6	Belarus	1	26	Montenegro	1
7	Brazil	2	27	Netherlands	3
8	Brunei	1	28	North Macedonia	4
9	Bulgaria	1	29	Poland	3
10	China	2	30	Qatar	4
11	Costa Rica	1	31	Saudi Arabia	3
12	Denmark	3	32	Serbia	4
13	Estonia	3	33	Singapore	3
14	Finland	3	34	South Africa	1
15	Georgia	4	35	Sweden	3
16	Hong Kong	3	36	Thailand	3
17	Iceland	3	37	Türkiye	4
18	Indonesia	4	38	United Arab Emirates	4
19	Kazakhstan	2	39	United Kingdom	3
20	Korea	3	40	United States	3

Figure 1 shows a cluster scatterplot in k-means clustering.

A cluster scatterplot in k-means clustering visualizes how the data points (countries) group together based on their values in three selected variables or dimensions. Each point represents a country, positioned according to its values on the three chosen indicators. Points close together mean those countries have similar profiles across those vari-

Source: Built in Statgraphics 19.

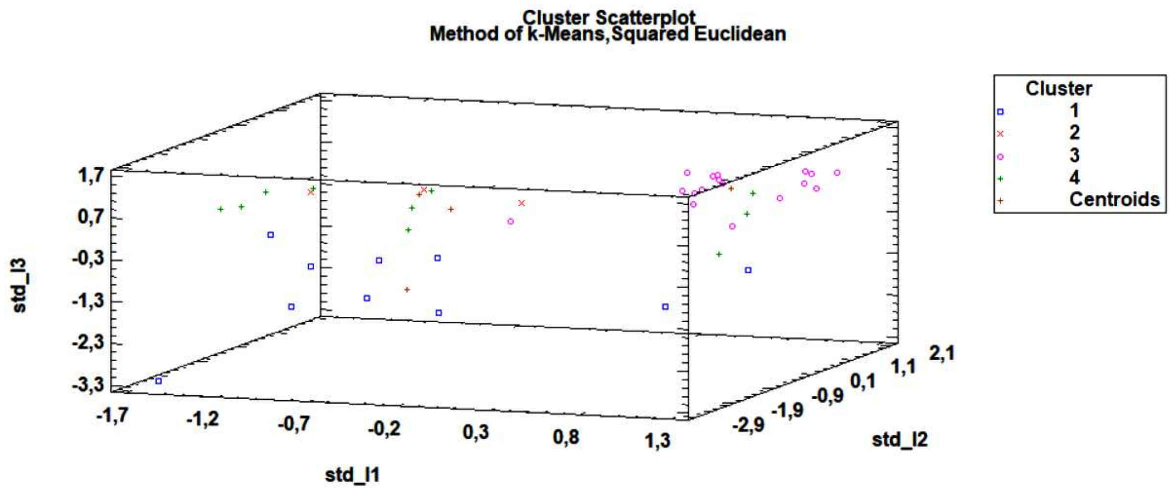

Figure 1. Cluster scatterplot in k-means clustering

ables. The points are colored or labeled by cluster membership (k = 4). The plot shows how well the k-means algorithm separated the countries into 4 groups based on the data. Often, the centroids (the mean position of each cluster in 3D space) are shown. They represent the "center" of each cluster and help summarize the average characteristics of that cluster. The plot reveals whether clusters are clearly separated (good clustering) or if some clusters overlap, which might suggest some countries are borderline or the chosen variables don't fully differentiate them.

Summary of clusters is in Table 4.

Table 4. Cluster summary

Cluster	Number of member countries	Countries' names
Cluster 1	10	Albania, Argentina, Belarus, Brunei, Bulgaria, Costa Rica, Kuwait, Libya, Montenegro, South Africa
Cluster 2	3	Brazil, China, Kazakhstan
Cluster 3	17	Australia, Denmark, Estonia, Finland, Hong Kong, Iceland, Korea, Latvia, Malaysia, Netherlands, Poland, Saudi Arabia, Singapore, Sweden, Thailand, United Kingdom, United States
Cluster 4	10	Azerbaijan, Bahrain, Georgia, Indonesia, Mauritius, North Macedonia, Qatar, Serbia, Türkiye, United Arab Emirates

Cluster 1 countries (Albania, Argentina, Belarus, Bulgaria, South Africa, etc.) are lower to moderate ICT and AI development scores. There are moderate financial services usage indicators. They are less advanced in GovTech maturity and cybersecurity, have limited digital payments and mobile/internet banking penetration, and are in a transition phase, with developing digital and financial infrastructures. For example, South Africa and Argentina have made strides but still lag behind Western Europe or North America.

Brazil, China, and Kazakhstan (Cluster 2) have a higher financial development index, with growing digital and financial ecosystems. There is a stronger performance on ICT and AI readiness, but possibly with challenges in GovTech (e.g., China's Digital Government strategies) or cybersecurity maturity. They are large emerging economies, showing strong mobile and internet banking activity, but with varied digital payments and financial inclusion rates. China leads globally in mobile payments. Brazil is rapidly growing in fintech usage. China and Brazil invest heavily but face complex cyber challenges. They are the countries where scale and rapid digital adoption are key features.

Cluster 3 (Australia, Denmark, Finland, United States, UK, Singapore, etc.) covers countries that score very high across almost all indicators: ICT development, AI preparedness, cybersecurity, GovTech maturity (e.g., Estonia's e-governance), and financial development. There is high usage of digital financial services, mobile payments, and advanced financial ecosystems, a high number of ATMs, and digital transactions reflecting a mature banking infrastructure. They represent highly developed economies with advanced digital and financial integration.

Azerbaijan, Bahrain, Georgia, Indonesia, Qatar, Türkiye, UAE, etc. (Cluster 4) are moderate to high on financial development and digital payments, driven by wealth from natural resources or rapid urbanization. There are moderate scores on AI and ICT development, but they are catching up quickly. These countries may show good GovTech maturity, especially in the Gulf states and emerging economies with significant investment in digital transformation. Cluster 4 reflects a group with rapidly growing but uneven digital financial ecosystems, possibly with high mobile usage but still developing infrastructure.

Key factors driving cluster membership are the following:

- Cluster 1: Developing ICT infrastructure, moderate financial inclusion, limited AI and GovTech maturity, lower digital financial usage.
- Cluster 2: Large economies with rapid digital financial sector growth, increasing GovTech maturity, and mixed cybersecurity.
- Cluster 3: Advanced ICT and AI readiness, mature financial systems, high GovTech and cybersecurity maturity, extensive digital payments.

http://dx.doi.org/10.21511/bbs.20(3).2025.06

- Cluster 4: Rapidly growing ICT and financial development, high mobile penetration, resource-driven investment in digital economies.

The global digitalization of the banking ecosystem is driven by converging trends in technology, regulation, inclusion, and human capital. From smart banking tools and fintech adoption to institutional transparency and cybersecurity, the transformation is multifaceted and interconnected. In the case of Azerbaijan, strategic investments in infrastructure, workforce development, and policy alignment are essential for integration into global digital clusters.

Cluster 4 membership suggests that Azerbaijan is part of a group of emerging digital economies that, while not yet matching the full digital maturity of high-income countries, demonstrate strong potential and active progress in key areas such as mobile banking adoption, digital payment penetration, and investments in government digital infrastructure.

Azerbaijan's clustering with countries like the UAE and Bahrain indicates a policy-driven digitalization trajectory, where strategic national digital transformation programs play a central role.

However, the analysis also implies the need for improvements in areas such as AI preparedness, cybersecurity robustness, and expansion of digital financial service access (e.g., credit card and loan account usage) to move closer to high-income digital benchmarks.

1. Strengthen AI and Cybersecurity Readiness.

While Azerbaijan has made significant progress in ICT infrastructure and GovTech services, greater investment is needed in developing AI strategies and strengthening national cybersecurity frameworks in line with global standards. This will ensure safe scaling of digital banking services.

2. Promote Financial Inclusion and Usage of Advanced Digital Services.

The country should focus on increasing access to and active use of credit cards, loan services, and online financial products, particularly among underbanked populations, by collaborating with fintech firms and financial institutions.

3. Expand Mobile and Internet Banking Penetration.

Azerbaijan should continue promoting the use of mobile banking applications and online payment platforms, especially in rural and less-digitized regions. Public campaigns and regulatory incentives can help build trust and increase adoption.

4. Foster Public-Private Partnerships (PPPs):

Leveraging PPPs in digital finance and infrastructure can attract global technology providers and support innovation in the banking sector.

5. Benchmark Against Regional Leaders.

Drawing on policy frameworks from fellow Cluster 4 countries like the UAE and Türkiye can help Azerbaijan identify successful practices in digital transformation, including regulatory innovation sandboxes, digital ID systems, and open banking frameworks.

These recommendations aim to help Azerbaijan transition from an emerging digital economy to a digitally mature and financially inclusive ecosystem, positioning itself closer to the standards of leading high-income digital economies.

Several notable works have also applied clustering techniques or other comparative methods to explore the digital development of banking systems across countries. For instance, Kolodiziev et al. (2022) conducted a cluster analysis of banks by the level of digitalization across 22 banks using multidimensional mathematical methods. Pakhnenko et al. (2021) investigated digitalization of financial services in EU countries based on 8 indicators and an integral index. Unlike studies limited to regional analyses or institutional level, this article presents a global comparative perspective and identifies convergence patterns between emerging and advanced economies in terms of digital banking development.

Recent global-scale studies have used machine learning techniques to analyze digital finance development globally, but focus primarily on high-income economies and fintech adoption rates. However, this approach includes silhouette analysis to validate cluster quality and applies a combined methodology using Stata, Statgraphics, and Python, which is rarely seen in earlier studies. What more differentiates this research from prior work is its dual focus on upper-middle- and high-income countries, integrating a broad set of 15 indicators that combine ICT infrastructure, AI preparedness, digital payment behavior, and financial services accessibility.

Despite its strengths, this study has several limitations:

- Sample size: The analysis covers only 40 countries, which limits the generalizability of findings to all income groups or geographic regions.
- Indicator availability: Some potentially relevant indicators, such as digital identity systems, were excluded due to data limitations.
- Temporal stativity: The study relies on cross-sectional data without accounting for trends or changes over time.
- Subjective exclusion: Armenia and the Russian Federation were excluded based on the authors' discretion.

Future research could address these limitations by expanding the country sample to include low-income and lower-middle-income countries, enabling a more comprehensive understanding of global digital banking patterns; by conducting longitudinal analyses to track changes in cluster membership over time and observe the impact of digital policy reforms; by incorporating qualitative dimensions, such as regulatory innovation (e.g., open banking laws, fintech regulation), to enrich the interpretation of clustering results; by exploring regional subsystems to identify region-specific dynamics and integration strategies.

CONCLUSION

The purpose of the article was to justify factors of linking upper-middle- and high-income countries in terms of banking ecosystem digitalization based on cluster analysis. The findings suggest that the digitalization of banking ecosystems is not determined solely by income classification but increasingly by policy orientation, digital infrastructure investment, and financial innovation adoption. This supports the hypothesis that upper-middle-income countries with strong digital strategies can converge with high-income economies in financial digitalization, offering new opportunities for inclusive financial growth and regulatory harmonization.

Key converging factors across clusters include ICT and GovTech maturity (a critical foundation for digital financial services), adoption of digital payments and mobile banking (a key behavioral driver of integration), AI preparedness and cybersecurity (emerging differentiators among more advanced clusters), government-led digital transformation strategies (particularly influential in non-Western high-performing cases, e.g., UAE, China, Brazil).

Countries were grouped into four distinct clusters. Azerbaijan's inclusion in the same cluster as countries such as the UAE and Bahrain highlights a policy-driven trajectory of digitalization, where comprehensive national strategies and government-led digital transformation programs play a pivotal role. Nonetheless, the analysis also reveals critical areas for development. To more closely align with high-income digital benchmarks, Azerbaijan must strengthen its capabilities in artificial intelligence readiness, enhance cybersecurity infrastructure, and expand access to digital financial services, particularly in the adoption of credit card usage and loan account penetration.

Future research could address the current study's limitations by expanding the dataset to include low- and lower-middle-income countries that would offer a more holistic view of global digital banking pat-

http://dx.doi.org/10.21511/bbs.20(3).2025.06

terns and support comparative analysis across income groups, and exploring regional banking ecosystems and digital integration strategies could reveal region-specific dynamics and help formulate more tailored policy recommendations.

AUTHOR CONTRIBUTIONS

Conceptualization: Sevinj Abbasova, Tetiana Vasylieva, Mehriban Aliyeva.
Data curation: Aybaniz Gubadova, Nigar Ashurbayli-Huseynova, Lala Kasumova.
Formal analysis: Sevinj Abbasova, Tetiana Vasylieva, Mehriban Aliyeva.
Funding acquisition: Aybaniz Gubadova, Nigar Ashurbayli-Huseynova, Lala Kasumova.
Investigation: Aybaniz Gubadova, Nigar Ashurbayli-Huseynova, Lala Kasumova.
Methodology: Sevinj Abbasova, Tetiana Vasylieva, Mehriban Aliyeva.
Project administration: Sevinj Abbasova, Aybaniz Gubadova, Lala Kasumova.
Resources: Tetiana Vasylieva, Mehriban Aliyeva, Nigar Ashurbayli-Huseynova.
Software: Aybaniz Gubadova, Nigar Ashurbayli-Huseynova, Lala Kasumova.
Supervision: Sevinj Abbasova, Aybaniz Gubadova.
Validation: Mehriban Aliyeva, Lala Kasumova.
Visualization: Nigar Ashurbayli-Huseynova, Lala Kasumova.
Writing – original draft: Mehriban Aliyeva, Aybaniz Gubadova, Lala Kasumova.
Writing – reviewing & editing: Sevinj Abbasova, Tetiana Vasylieva, Nigar Ashurbayli-Huseynova.

REFERENCES

1. Abou-Moghli, A. (2025). The role of strategic alignment and resource availability in boosting the digital capabilities of Jordanian insurance companies. *Insurance Markets and Companies, 16*(1), 74-89. https://doi.org/10.21511/ins.16(1).2025.07
2. Ahmed, M., Seraj, R., & Islam, S. M. S. (2020). The k-means Algorithm: A Comprehensive Survey and Performance Evaluation. *Electronics, 9*(8), 1295. https://doi.org/10.3390/electronics9081295
3. Al Afaishat, T., Al-Maadhedee, M., & Yamin, I. (2024). The impact of adopting the digital strategy on the competitive advantage: A moderating role of employee satisfaction in the Jordanian banking sector. *Problems and Perspectives in Management, 22*(1), 193-204. https://doi.org/10.21511/ppm.22(1).2024.17
4. Ali Mustafa, J. (2024). Integrating financial literacy, regulatory technology, and decentralized finance: A new paradigm in Fintech evolution. *Investment Management and Financial Innovations, 21*(2), 213-226. https://doi.org/10.21511/imfi.21(2).2024.17
5. Al-Smadi, O. M. (2025). Insurance sector readiness for digital transformation: Empirical evidence from Jordan. *Insurance Markets and Companies, 16*(1), 33-41. https://doi.org/10.21511/ins.16(1).2025.03
6. Annisa, S., Siahaan, E., & Lumbanraja, P. (2024). Impact of digital transformation on banking employee performance with self-efficacy as a mediator. *Problems and Perspectives in Management, 22*(4), 523-531. https://doi.org/10.21511/ppm.22(4).2024.39
7. Berisha, V., & Rayfield, B. (2025). Impact of internal fintech on bank profitability. *Investment Management and Financial Innovations, 22*(1), 384-404. https://doi.org/10.21511/imfi.22(1).2025.29
8. Dillianti, R., Prabowo, H., Kartono Rahim, R., & Kurniawan, Y. (2024). From readiness to excellence: The role of digital enablement and innovation in life insurance performance. *Insurance Markets and Companies, 15*(2), 35-46. https://doi.org/10.21511/ins.15(2).2024.04
9. DingYi, W., Yamaoka, Y, Sartamorn, S., & Oe, H. (2024). Can citizen Internet banking in China become a champion in the digital transformation era? *Financial Markets, Institutions and Risks, 8*(1), 16-30. https://doi.org/10.61093/fmir.8(1).16-30.2024
10. Dluhopolskyi, O., Pakhnenko, O., Lyeonov, S., Semenog, A., Artyukhova, N., Cholewa-Wiktor, M., & Jastrzębski, W. (2023). Digital Financial Inclusion: COVID-19 Impacts and Opportunities. *Sustainability, 15*(3), 2383. https://doi.org/10.3390/su15032383
11. Dobrovolska, O., & Kolomiiets, S. (2024). The Impact of Digitalisation on Social Determinants of Public Health. *Health Economics and Management Review, 5*(3), 128-142. https://doi.org/10.61093/hem.2024.3-09
12. Dobrovolska, O., & Rozhkova, M. (2024). The Impact of Digital Transformation on the Anti-Corruption and Cyber-Fraud System. *Business Ethics and Leadership, 8*(3), 231-252. https://doi.org/10.61093/bel.8(3).231-252.2024
13. Dobrovolska, O., Ortmanns, W., Dotsenko, T., Lustenko, V., & Sav-

chenko, D. (2024). Health Security and Cybersecurity: Analysis of Interdependencies. *Health Economics and Management Review, 5*(2), 84-103. https://doi.org/10.61093/hem.2024.2-06

14. Holtfort, T., & Horsch, A. (2024). Quantum Economics: A Systematic Literature Review. *SocioEconomic Challenges, 8*(1), 62-77. https://doi.org/10.61093/sec.8(1).62-77.2024

15. Hrytsenko, L., Pakhnenko, O. Kuzior, A., & Kozhushko, I. (2024). Smart technologies in banking. *Financial Markets, Institutions and Risks, 8*(1), 81-93. https://doi.org/10.61093/fmir.8(1).81-93.2024

16. Huseynov, A., Balsalobre-Lorente, D., Hamidova, L., & Samedova, E. (2025). Challenges and opportunities of digital economy development: Case of Azerbaijan. *Problems and Perspectives in Management, 23*(2), 265-276. https://doi.org/10.21511/ppm.23(2).2025.18

17. IMF. (n.d.a). *AI Preparedness Index (AIPI).* Retrieved from https://www.imf.org/external/datamapper/datasets/AIPI

18. IMF. (n.d.b). *Financial Access Survey (FAS) database*. Retrieved from https://data.imf.org/en/datasets/IMF.STA:FAS

19. IMF. (n.d.c). *Financial Development Index*. Retrieved from https://legacydata.imf.org/?sk=f8032e80-b36c-43b1-ac26-493c5b1cd33b

20. ITU. (n.d.). *ICT Development Index*. Retrieved from https://www.itu.int/en/ITU-D/Statistics/Pages/IDI/default.aspx

21. Ivashchenko, A., Britchenko, I., Dyba, M., Polishchuk, Y., Sybirianska, Y., & Vasylyshen, Y. (2018). Fintech platforms in SME's financing: EU experience and ways of their application in Ukraine. *Investment Management and Financial Innovations, 15*(3), 83-96. https://doi.org/10.21511/imfi.15(3).2018.07

22. Jain, A. K., Murty, M. N., & Flynn, P. J. (1999). Data clustering: A review. *ACM Computing Surveys, 31*(3), 264-323. http://doi.org/10.1145/331499.331504

23. Kadri, N. (2025). Factors Influencing Customers' Adoption of Electronic Banking Services in Commercial Banks. *Financial Markets, Institutions and Risks, 9*(1), 140-161. https://doi.org/10.61093/fmir.9(1).140-161.2025

24. Kolodiziev, O., Shcherbak, V., Vzhytynska, K., Chernovol, O., & Lozynska, O. (2022). Clustering of banks by the level of digitalization in the context of the COVID-19 pandemic. *Banks and Bank Systems, 17*(1), 80-93. https://doi.org/10.21511/bbs.17(1).2022.07

25. Krawczyk, D., Yefimenko, A., Pozovna, I., Riabyi, R., Huba, M., & Ponomarova O. (2025). International functional benchmarking model for bank capitalisation management in the context of securing macroeconomic stability: a case study of European countries. *Financial and Credit Activity Problems of Theory and Practice, 2*(61), 24-39. https://doi.org/10.55643/fcaptp.2.61.2025.4747

26. Kuzior, A., Brożek, P., Kuzmenko, O., Yarovenko, H., & Vasilyeva, T. (2022a). Countering Cybercrime Risks in Financial Institutions: Forecasting Information Trends. *Journal of Risk and Financial Management, 15*(12), 613. https://doi.org/10.3390/jrfm15120613

27. Kuzior, A., Marszałek-Kotzur, I., Kurovska, Y., & Chvankin, Y. (2024). The Role of Digital Economy in Transformation of Public Health: Modeling and Analysis. *Health Economics and Management Review,* 5(4), 91-109. https://doi.org/10.61093/hem.2024.4-06

28. Kuzior, A., Vasylieva, T., Kuzmenko, O., Koibichuk, V., & Brożek, P. (2022b). Global Digital Convergence: Impact of Cybersecurity, Business Transparency, Economic Transformation, and AML Efficiency. *Journal of Open Innovation: Technology, Market, and Complexity, 8*(4), 195. https://doi.org/10.3390/joitmc8040195

29. Lyeonov, S., Vasylieva, T., & Filatova, H. (2024). *Financial Fraud and Cybercrime in Wartime: An Overview of the Scientific Landscape and Insights from Countries Engaged in Military Conflict* (187 p.). The Academic Research and Publishing UG (i. G.). Hamburg, Germany, https://doi.org/10.61093/978-3-911748-02-5/2024

30. Lyeonov, S., Zakharkin, O., & Okhrimchuk, Y. (2023). Information Openness as a Factor of Business Leadership in Today's Digital Environment. In Strielkowski, W. (Ed.), *Leadership, Entrepreneurship and Sustainable Development Post COVID-19. NILBEC 2022* (pp. 287-300). Springer Proceedings in Business and Economics. Cham: Springer. https://doi.org/10.1007/978-3-031-28131-0_20

31. Maatallah, M. (2024). The Role of Digital Transformation in Enhancing Financial Inclusion: Unveiling the Economic and Social Challenges from Residents' Perspective. *SocioEconomic Challenges, 8*(3), 93-107. https://doi.org/10.61093/sec.8(3).93-107.2024

32. Minh Sang, N. (2024). Bibliometric insights into the evolution of digital marketing trends. *Innovative Marketing, 20*(2), 1-14. https://doi.org/10.21511/im.20(2).2024.01

33. Mourshoudli, F., Bykanova, N., & Evdokimov, D. (2020). Digitalization of the banking environment: formation of effective bank ecosystems. *Economic and Social Development: Book of Proceedings, 18,* 905-914. Retrieved from https://www.proquest.com/openview/e67c9e530fc61cafda43f4002ee9ec77/1

34. Mursalov, M., Yarovenko, H., & Vasilyeva, T. (2023). Entrepreneurial Ecosystem and Digitalization: Relationship and Synergy of Development. In Strielkowski, W. (Eds.), *Leadership, Entrepreneurship and Sustainable Development Post COVID-19. NILBEC 2022* (pp. 109-127). Springer Proceedings in Business and Economics. Cham: Springer. https://doi.org/10.1007/978-3-031-28131-0_9

35. Murshudli, F. F. (2018). Innovatsionnyye trendy mezhdunarodnogo bankovskogo biznesa (na primere Azerbaidzhana [Innovative Trends of International Banking Business (Case of Azerbaijan)].

http://dx.doi.org/10.21511/bbs.20(3).2025.06

MGIMO Review of International Relations, 1(58), 186-212. (In Russian). Retrieved from https://cyberleninka.ru/article/n/innovatsionnye-trendy-mezhdunarodnogo-bankovskogo-biznesa-na-primere-azerbaydzhana

36. Murshudli, F., & Loguinov, B. (2019). Digitalization challenges to global banking industry. *37th International Scientific Conference on Economic and Social Development – "Socio Economic Problems of Sustainable Development"* (pp. 786-794). Baku: VDEA – UNEC. Retrieved from https://www.esd-conference.com/upload/book_of_proceedings/Book_of_Proceedings_esdBaku2019_Online.pdf
37. Murshudli, F., & Loguinov, B. (2020). Transnationalization and Digitalization of Banks as Means of Evolving Efficiency Not Accountability. *55th International Scientific Conference on Economic and Social Development* (pp. 798-809). Baku: VDEA – UNEC. Retrieved from https://www.proquest.com/openview/23a1530f93b3b95637e706e34572f208/1
38. Okoli, T. T. (2024b). Financial technology adoption and bank stability among African economies: Is the relationship monotonic? *Investment Management and Financial Innovations, 21*(4), 385-399. https://doi.org/10.21511/imfi.21(4).2024.31
39. Pakhnenko, O., Rubanov, P., Hacar, D., Yatsenko, V., & Vida, I. (2021). Digitalization of financial services in European countries: Evaluation and comparative analysis. *Journal of International Studies, 14*(2), 267-282. https://doi.org/10.14254/2071-8330.2021/14-2/17
40. Polhemus, N. W. (n.d.). *Cluster Analysis using Statgraphics.* Retrieved from http://www.statvision.com/webinars/Cluster%20Analysis.pdf
41. Polishchuk, Y. (2023). Fintech future trends. In Lubacha, J., Maihaniemi, B., & Wisła, R. (Eds.), *The European digital economy* (pp. 204-220). Routledge. https://doi.org/10.4324/9781003450160-15
42. Shafranova, K., Navolska, N., & Koldovskyi, A. (2024). Navigating the digital frontier: a comparative examination of Central Bank Digital Currency (CBDC) and the Quantum Financial System (QFS). *SocioEconomic Challenges, 8*(1), 90-111. https://doi.org/10.61093/sec.8(1).90-111.2024
43. Statgraphics. (n.d.). *Introducing Statgraphics 19's new Python interface.* Retrieved from https://www.statgraphics.com/statgraphics-python-interface
44. Wang, F., Jia, Y., Li, G., Monica, L., & Liu, Y. (2024). An Empirical Study of the Relationship Between Digital Transformation, Corporate Social Responsibility and Financial Performance. *Business Ethics and Leadership, 8*(1), 57-73. https://doi.org/10.61093/bel.8(1).57-73.2024
45. World Bank. (n.d.a). *Digital Data Use.* Retrieved from https://data360.worldbank.org/en/indicator/WB_ID4D_DIG_DAT_BNRY
46. World Bank. (n.d.b). *Global Cybersecurity Index – Overall Score (ITU GCI).* Retrieved from https://data360.worldbank.org/en/indicator/ITU_GCI_GCI_OVRL_SCRE
47. World Bank. (n.d.c). *GovTech Maturity Index (GTMI) – Overall score.* Retrieved from https://data360.worldbank.org/en/indicator/WB_GTMI_GTMI
48. World Bank. (n.d.d). *Use of Financial Services, Credit cards.* Retrieved from https://data360.worldbank.org/en/indicator/IMF_FAS_FCCCC
49. World Bank. (n.d.e). *Use of Financial Services, Debit cards.* Retrieved from https://data360.worldbank.org/en/indicator/IMF_FAS_FCCDC
50. World Bank. (n.d.f). *Use of Financial Services, Deposit accounts.* Retrieved from https://data360.worldbank.org/en/indicator/IMF_FAS_FCAO
51. World Bank. (n.d.g). *Use of Financial Services, Loan accounts.* Retrieved from https://data360.worldbank.org/en/indicator/IMF_FAS_FCNO
52. World Bank. (n.d.h). *Used a mobile phone or the internet to buy something online.* Retrieved from https://genderdata.worldbank.org/en/indicator/fin14b-a
53. World Bank. (n.d.i). *Used a mobile phone or the internet to pay bills.* Retrieved from https://genderdata.worldbank.org/en/indicator/fin14a-a
54. Zhou, Y. (2024). The Business Leadership of the State-Owned Enterprises: Impact of the Digital Transformations. *Business Ethics and Leadership, 8*(3), 253-289. https://doi.org/10.61093/bel.8(3).253-289.2024

APPENDIX A

Table A1. Standardized variables for cluster analysis

Country	std_I1	std_I2	std_I3	std_I4	std_I5	std_I6	std_I7	std_I8	std_I9	std_I10	std_I11	std_I12	std_I13	std_I14	std_I15
Albania	–1,23	–0,54	–1,19	–0,04	–1,34	1,00	–0,94	–1,60	–0,09	–0,46	–0,75	–0,73	–0,63	–0,61	–0,17
Argentina	–1,25	–0,98	–2,00	0,02	–0,87	1,00	–0,39	–0,46	0,52	–0,10	0,51	0,85	0,24	–0,43	–0,18
Australia	0,65	1,11	0,71	0,31	1,89	1,00	1,36	1,26	–0,99	–0,62	0,47	0,42	1,17	–0,63	–0,18
Azerbaijan	–1,63	–1,00	0,24	0,08	–1,11	1,00	–1,29	–1,03	0,87	–0,62	0,04	–0,46	–0,63	–0,38	–0,17
Bahrain	1,03	–0,64	–0,42	0,43	–0,15	1,00	–0,90	–0,43	–0,99	–0,62	–1,15	–0,80	–0,62	–0,52	–0,18
Belarus	–0,43	–1,00	–1,98	–2,03	–1,52	1,00	–0,40	0,07	–0,99	–0,62	0,67	–0,76	–0,27	–0,13	–0,18
Brazil	–1,19	–0,75	0,66	1,25	0,76	1,00	–0,31	0,00	–0,37	3,00	–0,36	1,00	1,16	4,66	–0,15
Brunei	0,77	–0,80	–1,66	–0,57	–0,78	1,00	–1,73	–1,81	0,45	–0,02	0,33	–0,28	0,21	–0,63	–0,18
Bulgaria	–0,63	–0,13	–1,01	–0,45	–0,54	1,00	–0,12	–0,44	–0,04	–0,06	–0,23	–0,45	0,70	–0,45	–0,15
China	–0,81	0,35	0,42	–0,57	0,63	1,00	1,31	0,53	–0,17	4,36	4,66	0,21	0,18	–0,63	–0,18
Costa Rica	–0,88	–0,43	–1,01	–1,44	–0,95	1,00	–0,78	–0,35	0,46	0,43	0,29	0,12	–0,05	0,67	–0,15
Denmark	1,09	1,53	0,43	0,66	0,77	1,00	1,52	1,23	–0,99	–0,62	0,14	–0,31	–0,77	–0,06	–0,17
Estonia	1,09	1,41	0,82	1,19	–1,12	1,00	0,99	1,45	0,47	–0,02	0,01	–0,39	–0,17	0,43	–0,15
Finland	1,06	1,36	0,61	0,31	0,68	1,00	1,19	1,58	0,02	–0,62	0,34	0,58	–0,75	–0,63	6,16
Georgia	–0,70	–0,52	–0,23	–0,86	–0,75	1,00	–1,01	–0,47	0,71	0,56	0,79	–0,52	0,79	0,21	–0,14
Hong Kong	1,03	0,89	0,42	–0,39	1,21	1,00	0,87	0,93	–0,99	–0,62	–1,15	3,67	–0,46	–0,63	–0,18
Iceland	0,77	0,88	–0,30	0,66	0,00	1,00	0,92	1,19	2,36	1,05	–0,38	0,43	–0,27	–0,63	–0,18
Indonesia	–1,46	–0,63	0,56	0,37	–0,60	1,00	–1,06	–1,47	0,38	0,04	–0,19	–0,68	–0,48	–0,15	–0,16
Kazakhstan	–0,12	–0,33	0,46	0,37	–0,65	1,00	–0,02	0,41	–0,99	1,49	1,76	0,46	0,63	1,89	–0,17
Korea	0,62	1,10	0,77	1,36	1,47	1,00	1,18	0,68	3,00	–0,62	–0,63	3,23	4,85	0,51	–0,10
Kuwait	1,29	–1,08	–0,58	–0,74	–0,44	1,00	–1,02	–0,56	–0,99	–0,28	–0,12	–0,30	0,06	–0,63	–0,18
Latvia	0,62	0,33	0,70	0,60	–1,30	1,00	0,73	1,35	0,07	–0,62	–0,32	–0,34	–0,22	0,39	–0,14
Libya	–1,57	–2,86	–3,22	–3,72	–1,69	1,00	–1,27	–1,42	–0,99	–0,46	–0,94	–0,80	–1,21	–0,52	–0,18
Malaysia	0,73	0,32	0,74	0,19	1,06	1,00	0,51	0,02	0,17	0,13	0,29	–0,24	–0,33	0,34	–0,14
Mauritius	–1,22	–0,56	0,67	0,60	–0,01	1,00	–0,91	–0,93	–0,96	–0,36	0,05	–0,47	–0,58	–0,16	–0,11
Montenegro	–0,88	–0,73	–1,82	–1,15	–0,01	1,00	–1,04	–1,34	–0,04	–0,08	–0,41	–0,71	0,47	–0,52	–0,16
Netherlands	0,58	1,43	0,68	0,02	0,97	1,00	1,31	1,14	0,13	0,07	0,50	–0,08	–0,79	0,67	–0,02
North Macedonia	–1,54	–0,91	0,27	–1,09	–1,08	1,00	–0,36	–0,43	0,21	0,15	–0,35	–0,50	0,06	–0,49	–0,15
Poland	0,74	0,03	0,50	–0,45	–0,30	1,00	1,10	1,08	0,74	0,53	–0,23	–0,56	0,15	0,18	–0,09
Qatar	1,16	–0,48	0,54	0,66	0,15	1,00	–1,73	–1,81	–0,99	–0,62	–1,15	–0,80	–0,06	–0,63	–0,18
Saudi Arabia	0,79	–0,13	0,83	1,25	–0,25	1,00	0,60	0,62	0,07	–0,19	0,09	–0,62	–0,17	–0,08	–0,17
Serbia	–0,70	–0,45	0,27	0,84	–1,10	1,00	–0,15	–0,34	–0,99	0,20	0,16	–0,55	–0,27	–0,37	–0,15
Singapore	1,17	1,71	0,77	0,43	0,95	1,00	0,75	0,75	–0,99	–0,62	0,65	1,21	–0,44	–0,63	–0,18
South Africa	–1,40	–0,79	–0,38	–1,15	0,23	1,00	–1,18	–0,57	0,30	–0,62	–1,15	–0,80	–0,37	–0,63	–0,18
Sweden	0,64	1,28	0,54	–0,04	1,28	1,00	1,42	1,40	1,13	–0,62	–0,16	0,35	–1,02	0,90	–0,16
Thailand	–0,15	–0,47	0,08	0,72	1,08	1,00	0,18	–0,02	0,09	–0,16	–0,36	–0,17	0,83	1,94	–0,15
Türkiye	–0,60	–0,43	0,71	0,66	0,02	1,00	–0,37	0,13	2,50	–0,62	0,87	1,45	0,39	0,30	–0,16
United Arab Emirates	1,02	0,29	0,74	1,19	–0,05	1,00	–0,78	–1,18	–0,15	0,10	–0,28	0,00	–0,18	–0,63	–0,18
United Kingdom	0,47	1,14	0,83	0,49	1,56	1,00	0,66	0,09	–0,99	–0,62	–1,15	–0,80	0,49	–0,63	–0,18
United States	1,05	1,47	0,85	0,08	1,93	1,00	1,14	0,76	–0,99	–0,62	–1,15	–0,80	–1,64	–0,63	–0,18

Note: stdI1-stdI15 – indicators values after standardization; I1 – ICT Development Index overall score; I2 – AI Preparedness Index overall score; I3 – Global Cybersecurity Index overall score; I4 – GovTech Maturity Index; I5 – Financial Development Index; I6 – Digital Data Use Indicator; I7 – Using Mobile Phone / the Internet for online purchase; I8 – Using Mobile Phone / the Internet to Pay Bills; I9 – Using Financial Services – Deposit Accounts; I10 – Using Financial Services – Loan accounts; I11 – Using Financial Services – Debit cards; I12 – Using Financial Services – Credit cards; I13 – Number of automated teller machines; I14 – Number of mobile and internet banking transactions; I15 – Value of mobile and internet banking transactions (% of GDP).

http://dx.doi.org/10.21511/bbs.20(3).2025.06

APPENDIX B

Table B1. Intermediate results of cluster analysis using the k-means method for two clusters (k = 2)

Cluster Summary

Cluster	Members	Percent
1	19	47.50
2	21	52.50

Centroids

Cluster	std_I1	std_I2	std_I3	std_I4	std_I5	std_I6	std_I7	std_I8
1	−0.539902	−0.748904	−0.642709	−0.477943	−0.664642	1.0	−0.897014	−0.872899
2	0.488482	0.677579	0.581498	0.432424	0.601343	1.0	0.811584	0.789766

Cluster	std_I9	std_I10	std_I11	std_I12	std_I13	std_I14	std_I15
1	−0.174126	−0.180662	−0.203775	−0.456533	−0.148275	−0.368843	−0.165359
2	0.157542	0.163456	0.184368	0.413054	0.134154	0.333715	0.149611

Note: stdI1-stdI15 – indicator values after standardization.

Table B2. Intermediate results of cluster analysis using the k-means method for three clusters (k = 3)

Cluster Summary

Cluster	Members	Percent
1	19	47,50
2	3	7,50
3	18	45,00

Centroids

Cluster	std_I1	std_I2	std_I3	std_I4	std_I5	std_I6	std_I7	std_I8
1	−0.539902	−0.748904	−0.642709	−0.477943	−0.664642	1.0	−0.897014	−0.872899
2	−0.70681	−0.243327	0.513638	0.348891	0.245753	1.0	0.328915	0.312989
3	0.687698	0.831064	0.592808	0.446347	0.660608	1.0	0.892029	0.869229

Cluster	std_I9	std_I10	std_I11	std_I12	std_I13	std_I14	std_I15
1	−0.174126	−0.180662	−0.203775	−0.456533	−0.148275	−0.368843	−0.165359
2	−0.50807	2.94624	2.01701	0.556607	0.656176	1.97276	−0.168369
3	0.268478	−0.300341	−0.121072	0.389128	0.0471503	0.0605404	0.202607

Note: stdI1-stdI15 – indicator values after standardization.

Table B3. Intermediate results of cluster analysis using the k-means method for four clusters (k = 4)

Cluster Summary

Cluster	Members	Percent
1	10	25,00
2	3	7,50
3	17	42,50
4	10	25,00

Centroids

Cluster	std_I1	std_I2	std_I3	std_I4	std_I5	std_I6	std_I7	std_I8
1	−0.621059	−0.934181	−1.48573	−1.12854	−0.792237	1.0	−0.886414	−0.848424
2	−0.70681	−0.243327	0.513638	0.348891	0.245753	1.0	0.328915	0.312989
3	0.763161	0.905334	0.585998	0.433735	0.698582	1.0	0.966032	0.912491
4	−0.464272	−0.531889	0.33544	0.286519	−0.469078	1.0	−0.854515	−0.796707

Cluster	std_I9	std_I10	std_I11	std_I12	std_I13	std_I14	std_I15
1	−0.14058	−0.227708	−0.178855	−0.389115	−0.0837549	−0.388486	−0.171307
2	−0.50807	2.94624	2.01701	0.556607	0.656176	1.97276	−0.168369
3	0.136922	−0.281569	−0.179214	0.326907	0.0267503	0.0463129	0.223764
4	0.0602341	−0.177496	−0.121583	−0.333609	−0.158573	−0.282075	−0.158582

Note: stdI1-stdI15 – indicator values after standardization.

Table B4. Intermediate results of cluster analysis using the k-means method for five clusters (k = 5)

Cluster Summary		
Cluster	**Members**	**Percent**
1	9	22,50
2	3	7,50
3	14	35,00
4	7	17,50
5	7	17,50

Centroids								
Cluster	**std_I1**	**std_I2**	**std_I3**	**std_I4**	**std_I5**	**std_I6**	**std_I7**	**std_I8**
1	−0.83366	−0.91792	−1.58684	−1.17142	−0.831009	1.0	−0.871642	−0.880488
2	−0.70681	−0.243327	0.513638	0.348891	0.245753	1.0	0.328915	0.312989
3	0.836777	1.11871	0.597277	0.343322	0.882108	1.0	1.06542	0.969072
4	−1.12143	−0.642414	0.356002	0.0843687	−0.663981	1.0	−0.732998	−0.649746
5	0.822642	−0.310549	0.26953	0.585569	−0.137118	1.0	−0.418127	−0.29048

Cluster	std_I9	std_I10	std_I11	std_I12	std_I13	std_I14	std_I15
1	−0.0464613	−0.222029	−0.185731	−0.398526	−0.100159	−0.361366	−0.170396
2	−0.50807	2.94624	2.01701	0.556607	0.656176	1.97276	−0.168369
3	0.149767	−0.272513	−0.175269	0.477566	0.00133059	−0.104316	0.304541
4	0.389254	−0.0909628	0.194093	−0.246397	−0.10292	−0.147508	−0.149685
5	−0.411309	−0.34122	−0.469189	−0.434891	−0.0521843	−0.0247146	−0.168158

Note: stdI1-stdI15 – indicator values after standardization.

Table B5. Intermediate results of cluster analysis using the k-means method for six clusters (k = 6)

Cluster Summary		
Cluster	**Members**	**Percent**
1	7	17,50
2	3	7,50
3	14	35,00
4	7	17,50
5	7	17,50
6	2	5,00

Centroids								
Cluster	**std_I1**	**std_I2**	**std_I3**	**std_I4**	**std_I5**	**std_I6**	**std_I7**	**std_I8**
1	−0.786544	−0.628425	−1.29749	−0.684138	−0.611135	1.0	−0.882069	−0.938813
2	−0.70681	−0.243327	0.513638	0.348891	0.245753	1.0	0.328915	0.312989
3	0.836777	1.11871	0.597277	0.343322	0.882108	1.0	1.06542	0.969072
4	−1.12143	−0.642414	0.356002	0.0843687	−0.663981	1.0	−0.732998	−0.649746
5	0.822642	−0.310549	0.26953	0.585569	−0.137118	1.0	−0.418127	−0.29048
6	−0.998566	−1.93115	−2.59956	−2.87689	−1.60057	1.0	−0.835149	−0.676349

Cluster	std_I9	std_I10	std_I11	std_I12	std_I13	std_I14	std_I15
1	0.222449	−0.130665	−0.2009	−0.288411	0.0820547	−0.372148	−0.168075
2	−0.50807	2.94624	2.01701	0.556607	0.656176	1.97276	−0.168369
3	0.149767	−0.272513	−0.175269	0.477566	0.00133059	−0.104316	0.304541
4	0.389254	−0.0909628	0.194093	−0.246397	−0.10292	−0.147508	−0.149685
5	−0.411309	−0.34122	−0.469189	−0.434891	−0.0521843	−0.0247146	−0.168158
6	−0.987646	−0.541804	−0.132638	−0.78393	−0.737905	−0.32363	−0.178518

Note: stdI1-stdI15 – indicator values after standardization.

http://dx.doi.org/10.21511/bbs.20(3).2025.06

Table B6. Intermediate results of cluster analysis using the k-means method for seven clusters (k = 7)

Cluster Summary		
Cluster	**Members**	**Percent**
1	4	10,00
2	4	10,00
3	14	35,00
4	6	15,00
5	7	17,50
6	2	5,00
7	3	7,50

Centroids

Cluster	std_I1	std_I2	std_I3	std_I4	std_I5	std_I6	std_I7	std_I8
1	−0.686514	−0.715841	−1.26386	−0.727993	−0.478498	1.0	−1.22101	−1.32944
2	−0.865373	−0.512966	−1.06468	−0.684138	−0.778297	1.0	−0.57442	−0.431478
3	0.836777	1.11871	0.597277	0.343322	0.882108	1.0	1.06542	0.969072
4	−1.19138	−0.663441	0.453959	0.24169	−0.649773	1.0	−0.687291	−0.679377
5	0.822642	−0.310549	0.26953	0.585569	−0.137118	1.0	−0.418127	−0.29048
6	−0.998566	−1.93115	−2.59956	−2.87689	−1.60057	1.0	−0.835149	−0.676349
7	−0.70681	−0.243327	0.513638	0.348891	0.245753	1.0	0.328915	0.312989

Cluster	std_I9	std_I10	std_I11	std_I12	std_I13	std_I14	std_I15
1	0.153685	−0.295896	−0.493642	−0.634331	−0.080103	−0.599291	−0.174138
2	0.413198	0.208351	0.339659	0.0007995	0.421012	0.00147225	−0.155647
3	0.149767	−0.272513	−0.175269	0.477566	0.00133059	−0.104316	0.304541
4	0.335732	−0.200203	0.0947127	−0.201588	−0.251615	−0.20772	−0.150864
5	−0.411309	−0.34122	−0.469189	−0.434891	−0.0521843	−0.0247146	−0.168158
6	−0.987646	−0.541804	−0.132638	−0.78393	−0.737905	−0.32363	−0.178518
7	−0.50807	2.94624	2.01701	0.556607	0.656176	1.97276	−0.168369

Note: stdI1-stdI15 – indicator values after standardization.

Table B7. Intermediate results of cluster analysis using the k-means method for eight clusters (k = 8)

Cluster Summary		
Cluster	**Members**	**Percent**
1	3	7,50
2	4	10,00
3	14	35,00
4	6	15,00
5	7	17,50
6	2	5,00
7	3	7,50
8	1	2,50

Centroids

Cluster	std_I1	std_I2	std_I3	std_I4	std_I5	std_I6	std_I7	std_I8
1	−1.17362	−0.68737	−1.13133	−0.781594	−0.376376	1.0	−1.05185	−1.17017
2	−0.865373	−0.512966	−1.06468	−0.684138	−0.778297	1.0	−0.57442	−0.431478
3	0.836777	1.11871	0.597277	0.343322	0.882108	1.0	1.06542	0.969072
4	−1.19138	−0.663441	0.453959	0.24169	−0.649773	1.0	−0.687291	−0.679377
5	0.822642	−0.310549	0.26953	0.585569	−0.137118	1.0	−0.418127	−0.29048
6	−0.998566	−1.93115	−2.59956	−2.87689	−1.60057	1.0	−0.835149	−0.676349
7	−0.70681	−0.243327	0.513638	0.348891	0.245753	1.0	0.328915	0.312989
8	0.774802	−0.801253	−1.66145	−0.567191	−0.784863	1.0	−1.7285	−1.80723

Table B7 (cont.). Intermediate results of cluster analysis using the k-means method for eight clusters (k = 8)

Cluster	std_I9	std_I10	std_I11	std_I12	std_I13	std_I14	std_I15
1	0.0563169	−0.388623	−0.767942	−0.750803	−0.175408	−0.588201	−0.172348
2	0.413198	0.208351	0.339659	0.0007995	0.421012	0.00147225	−0.155647
3	0.149767	−0.272513	−0.175269	0.477566	0.00133059	−0.104316	0.304541
4	0.335732	−0.200203	0.0947127	−0.201588	−0.251615	−0.20772	−0.150864
5	−0.411309	−0.34122	−0.469189	−0.434891	−0.0521843	−0.0247146	−0.168158
6	−0.987646	−0.541804	−0.132638	−0.78393	−0.737905	−0.32363	−0.178518
7	−0.50807	2.94624	2.01701	0.556607	0.656176	1.97276	−0.168369
8	0.445788	−0.0177161	0.329261	−0.284915	0.205813	−0.632561	−0.179507

Note: stdI1-stdI15 – indicator values after standardization.

http://dx.doi.org/10.21511/bbs.20(3).2025.06