“National readiness for the transformation of digital banking from mobile applications to AI-driven services: A cross-country composite index”

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NATIONAL READINESS FOR THE TRANSFORMATION OF DIGITAL BANKING FROM MOBILE APPLICATIONS TO AI-DRIVEN SERVICES: A CROSS-COUNTRY COMPOSITE INDEX

Abstract

The digital transformation of banking is entering a new phase, shifting from mobile applications toward AI-driven, personalized services, yet the readiness of national environments for this shift remains largely unexamined. The study aims to assess the cross-country readiness of banking systems for this shift by integrating demand-side digital financial inclusion with supply-side government AI readiness in a single composite measure. To this end, an AI-Banking Readiness Index (ABRI) is constructed by two-stage principal-component analysis from the World Bank Global Findex (2011–2024) and the Oxford Insights Government AI Readiness Index 2025 for 97 economies; it is complemented by k-means clustering, a demand–supply positioning matrix, and cross-sectional and two-way fixed-effects panel regressions. Three findings follow. First, at the index level, the two sides of readiness are only moderately aligned ($r = 0.655$), and 28 of the 97 economies lead on one side only – a mismatch that supply-only rankings conceal. Second, across countries, government AI readiness is positively associated with deeper household digital-finance adoption once income is controlled ($\beta = 0.451$, $p = 0.017$). Third, within countries over time, e-government capacity is related to account ownership in a pattern consistent with an infrastructure-mediated channel; this constitutes suggestive channel evidence rather than a formal mediation test. Practically, the index locates each economy’s binding constraint: supply-led economies need demand-side activation through connectivity, interoperable payments, and digital literacy, whereas demand-led economies need AI governance and supervisory capacity before personalized, AI-driven services can scale safely.

Keywords digital banking, financial inclusion, AI readiness, composite index, panel data, cluster analysis, cross-country, e-government

JEL Classification G21, O38, C43, C23

INTRODUCTION

Over the past decade, digital technology has reshaped how households interact with banks. Worldwide account ownership rose from 51% of adults in 2011 to 79% in 2024, and in low- and middle-income economies it reached 75%, up from 42% (Klapper et al., 2025). Mobile phones and the internet account for much of this growth: 62% of adults in developing economies – 82% of account owners – made or received a digital payment in 2024, and the share saving formally in an account climbed to 40%, a 16-percentage-point increase since 2021 (Klapper et al., 2025; OECD, 2025). For a growing majority of customers, the mobile application has become the primary banking channel. Yet 1.3

billion adults remain unbanked, and persistent gaps in usage, gender, and income mean that the digital transformation of banking is far from complete (Klapper et al., 2025).

A second wave of transformation is now underway as banks move from app-based self-service toward AI-mediated, personalized services – conversational assistants, automated advice, and real-time fraud monitoring. The McKinsey Global Institute estimates that generative AI could add USD 200-340 billion annually to the global banking sector, equivalent to 2.8-4.7% of industry revenues, largely through productivity gains and richer customer interaction (McKinsey Global Institute, 2023). Realizing this potential depends not only on customer demand but also on the institutional and policy environment in which banks operate – data infrastructure, digital skills, regulation, and public-sector AI capacity (Bagirzade, 2025). That environment is highly uneven: the Government AI Readiness Index 2025 assesses 195 governments across six pillars and 14 dimensions and finds wide, persistent disparities, with high-income leaders such as the United States, France, and the United Kingdom far ahead of most low- and middle-income economies (Oxford Insights, 2025). Readiness for the next, AI-driven stage of digital banking is thus unequally distributed across countries.

Two clarifications delimit the scope. The unit of observation is the country: the study measures the readiness of the environment in which a national banking system operates (the demand-side maturity of household digital finance and the supply-side capacity of the state to enable AI), not the AI services of individual banks, so bank-level applications such as chatbots, robo-advisory, or AI-based credit scoring are not observed here. Readiness is thus understood as the set of macro-level preconditions under which AI-driven banking services can emerge and scale, not as a measure of how far banks have already deployed them.

These two dimensions – the demand-side maturity of digital finance and the supply-side capacity of the state to enable AI – have so far been studied largely in isolation. The financial-inclusion literature documents how account ownership and digital payments spread, while a separate strand assesses national AI readiness; few studies connect the customer-facing footprint of digital banking with the AI policy frameworks that shape its next phase, and integrated composite metrics that bridge these two domains remain limited. This gap matters because a banking system's readiness for AI-driven, personalized services is jointly determined by how broadly customers already engage with digital channels and by how prepared the surrounding governance environment is to deploy AI responsibly. This study addresses that gap by constructing a composite AI-Banking Readiness Index (ABRI) that brings both sides of readiness into a single instrument.

The primary contribution of this study is integrative rather than technical. The true value of the ABRI lies not in proposing a novel weighting scheme, but in synthesizing demand- and supply-side metrics into a unified framework. To demonstrate its practical diagnostic utility, the index is computed for all 97 economies, and its interpretation is then illustrated for one regional group – Armenia, Azerbaijan, Georgia, Kazakhstan, Uzbekistan, and Türkiye – that spans the full demand–supply typology developed below.

1. LITERATURE REVIEW

The digitalization of financial services has shifted from incremental improvements in service delivery to the creation of fundamentally new business models, products, and modes of customer interaction (Gomber et al., 2017), and a growing body of work now treats artificial intelligence (AI) as the next inflection point in this trajectory (Singh et al., 2025). Evidence on the performance consequences for incumbents is conditional rather than uniform: across European Union banks, FinTech and AI adoption operate as a double-edged sword, raising returns for well-capitalized, technologically mature institutions while exposing weaker ones to integration risk (Siminică et al., 2025), and

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the launch of generative tools such as ChatGPT produced a significant negative reaction in the stock returns of traditional commercial banks (Beckmann & Hark, 2024). At the consumer interface, readiness to adopt FinTech and AI-driven finance depends heavily on baseline digital literacy, financial literacy, and self-efficacy (Dewi et al., 2025; Islam & Khan, 2024), foreshadowing the demand-side constraints examined below. The review that follows is therefore organized around the two sides of the proposed index (demand-side adoption and supply-side state capacity) together with the composite-indicator methodology that joins them.

A large stream models the micro-determinants of digital-banking adoption and the customer experience it produces. Perceived usefulness, ease of use, security, and trust consistently emerge as the principal drivers of intention to use and of customer satisfaction (Hedau, 2025; Kadri, 2025; Lama et al., 2025), with satisfaction in turn mediating long-run loyalty to digital wallets and mobile services (Thi Nguyen et al., 2026) and ubiquitous mobile-internet access acting as a structural enabler of mobile-banking uptake (Malaquias & Hwang, 2025). These benefits are unevenly distributed, however: older adults face technological and trust barriers that require tailored interfaces (Poorna Chandran & Tholath, 2025). A related literature studies the AI layer of the customer relationship – conversational agents, recommendation systems, sentiment-based feedback analytics, and chatbots (Peruchini et al., 2024; Kildei et al., 2025; Kostiushko et al., 2025) – and finds that while AI quality and prior experience predict the intention to use robo-advisory services, consumers retain a marked preference for human fallback and remain skeptical of full automation in complex or sensitive interactions (Piotrowski & Orzeszko, 2023; Glos & Karwot, 2025). Collectively, this body of literature establishes that while adoption is constrained by trust and literacy at the individual level, the focus remains inherently micro-analytic. It fails to identify which countries possess the necessary demand base for AI-driven banking. The demand sub-index developed below is specifically designed to bridge this aggregation gap.

At the macro level, the diffusion of mobile technology has driven historic growth in account ownership, digital payments, and mobile money (Klapper et al., 2025), and FinTech is widely identified as a catalyst that extends inclusion in emerging markets by circumventing legacy infrastructure (Murshudli & Loguinov, 2019, 2020; Murshudli et al., 2020; Kovalenko, 2021, Kovalenko et al., 2023, Del Sarto & Ozili, 2025). The welfare consequences are more contested. Expanding financial access raises bank profitability but introduces stability and socio-economic trade-offs (Budhathoki et al., 2025), and the link between inclusion and poverty or inequality is non-linear, materializing only once digital-payment usage passes certain thresholds (Laskienė et al., 2026) – a reminder that inclusion depends on literacy and institutional support rather than access alone.

A separate, largely macro-institutional stream measures the supply side – national capacity, infrastructure, and governance for AI – frequently operationalized through the Government AI Readiness Index (GARI). National-level AI readiness, in its ethics, institutions, infrastructure, and governance components (Bagirzade, 2023), is found to drive banking-sector profitability and transformation (Sitnicka et al., 2025). Evidence from adjacent, similarly infrastructure-dependent domains reinforces the interpretation of the GARI as a general-purpose state capability rather than a sector-specific one: government AI readiness has been linked to renewable-energy capacity, energy security, and energy equity (Lyeonov et al., 2025; Kuzior et al., 2025a; Kirichok et al., 2025; Yarovenko et al., 2025a). It is this portability across sectors that motivates extending the index to banking, although these studies observe institutional outcomes rather than the household side of the markets concerned. More broadly, e-government development and network readiness strengthen states' capacity to combat corruption and cyber threats (Yarovenko et al., 2025a), institutional trust mediates the conversion of digital maturity into infrastructure outcomes (Topazly et al., 2026), and the realization of public-sector AI value depends on change management, public–private partnerships, and reasonable human oversight (Barodi & Lalaoui, 2025; Oe et al., 2025; Kajda & Karwot, 2025; Hayes & Burrell, 2026). Cross-national evidence also documents persistent unevenness in public-sector digital transformation that early infrastructure advantages do not guarantee away (Valaskova et al., 2025), and clustering of compliance regimes underscores the need for context-specific institutional strategies (Kuzior et al., 2025b).

Underpinning both sides is a literature on digital transformation as an economy- and firm-level process. Digital enablement and open innovation restructure firm value and sustainability when matched by supportive organizational culture (Dillianti et al., 2024; Elmaghraby et al., 2025), yet financial constraints stratify rather than converge digital capabilities among smaller firms (Sartamorn et al., 2025), and workforce resistance must be managed for AI integration to succeed (Hart, 2025). At the country level, clustering and multi-criteria methods reveal latent structures and persistent divides in digital-transformation trajectories driven more by digital competence and human capital than by basic ICT (Pakhnenko et al., 2025; Yarovenko et al., 2025b), while AI investment and research activity emerge as engines of national innovation (Temerbulatova et al., 2025). This stream also flags cross-cutting risks and tools: opaque algorithmic profiling and weak user awareness on digital platforms (Wieczorek & Postrzednik-Lotko, 2025; Hayes, 2026), the trust dynamics of AI disclosure (Pho Nguyen et al., 2026), the sustainability potential of AI-enabled collaboration (Quisenberry & Burrell, 2026), AI's promise for regulatory surveillance (Burrell, 2025), and – methodologically central to the present study – the design of robust composite indicators, where weighting and aggregation choices are the principal sources of fragility (Greco et al., 2019). The central prescription of this stream is that the credibility of a composite indicator rests less on the sophistication of its weighting scheme than on the transparency and robustness of its construction – a principle that directly guides the design choices of the present study.

Taken together, the reviewed evidence locates the drivers of digital-banking adoption at the household level and the enabling capacity for AI at the level of the state, but it examines the two largely on different units of analysis, with different data, and in static designs. Country-level instruments that read both sides jointly are still lacking, as is evidence on how the relationship between them unfolds within countries over time.

This study aims to assess the cross-country readiness of banking systems for the shift toward AI-driven, personalized services by constructing a composite AI-Banking Readiness Index that integrates demand-side digital financial inclusion with supply-side government AI readiness, classifying economies by their demand–supply profiles, and estimating how AI readiness relates to household digital-finance maturity across countries and over time.

2. DATA AND METHODOLOGY

This section describes the data and sample (Section 2.1), defines the variables (Section 2.2), formalizes the construction of the AI-Banking Readiness Index, ABRI (Section 2.3), sets out the empirical strategy (Section 2.4), and states the study's limitations (Section 2.5).

2.1. Data and sample

The analysis combines four public sources. Demand-side digital-finance behavior is drawn from the World Bank Global Findex Database (2025 release), which reports nationally representative survey indicators for five waves (2011, 2014, 2017, 2021, and 2024); the cross-sectional analysis uses the latest (2024) wave, while the panel exploits all five. Supply-side AI capacity is measured by the Oxford Insights Government AI Readiness Index (GARI) 2025, comprising an overall score and six pillars. Because the GARI is a single cross-sectional snapshot, the United Nations E-Government Development Index (EGDI) – a biennial, time-varying measure of state digital capacity – serves as the panel proxy for the supply side. Three considerations justify this substitution. Conceptually, the EGDI measures the same latent state digital capacity on which AI readiness builds: its online-services, telecommunication-infrastructure, and human-capital components capture the infrastructural and public-sector foundations underlying the GARI pillars. Empirically, the two measures are strongly convergent in this sample ($r \approx 0.82$; Section 3.6). Pragmatically, the EGDI is the only near-universal, biennial, time-varying indicator of state digital capacity spanning 2011–2024. Because the EGDI is nonetheless broader than AI readiness, the panel estimates are interpreted

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throughout as evidence on e-government capacity rather than on AI readiness specifically. Macro-financial controls are taken from the World Bank World Development Indicators (WDI) and Worldwide Governance Indicators (WGI), supplemented by the International Telecommunication Union (ITU) for connectivity variables.

Since each analytical stage entails distinct data requirements, the resulting samples differ in a transparent, largely nested manner (summarized in Table B1, Appendix B). Constructing the ABRI requires the intersection of economies included in the 2024 Findex wave (possessing complete digital-finance indicators) and the 2025 GARI, yielding 97 economies (listed in Table B2, Appendix B). The cross-sectional regressions are estimated on the 93 economies from this group that have complete control variables. Conversely, the panel analysis is not constrained by GARI coverage; it strictly requires data on account ownership (available across all five Findex waves), the EGDI, and WDI/WGI controls, all of which offer broader geographic coverage. This formulation yields 648 complete country-wave cases. After excluding nine singleton country effects, the final estimation sample comprises 639 observations across 142 countries, each observed in at least two waves. Ninety-one of the 97 ABRI economies are included in this panel (six were excluded due to appearing in fewer than two complete Findex waves). Consequently, the panel nests the index sample while incorporating an additional 51 economies that lack complete ABRI inputs. Finally, the AI-specific trend specification restricts the panel exclusively to GARI-covered countries (423 observations across 94 countries). Ultimately, the broader panel addresses within-country dynamics, whereas all index-based findings rely on the 97-economy sample.

All index-based results are reported for the full 97-economy sample. To show how the index is read in practice, one regional group – Armenia, Azerbaijan, Georgia, Kazakhstan, Uzbekistan, and Türkiye – is used as a worked example: these economies share a common institutional legacy and comparable development trajectories, with low financial inclusion in the early 2010s followed by rapid digitalization, and together they span the full demand–supply typology developed below. The group serves purely as an illustration; all estimation results in Sections 3.5 and 3.6 are based on the full samples described above.

2.2. Variables

Appendix A defines the variables and their sources. The demand block comprises three Findex indicators – digitally enabled account ownership, digital payment activity, and formal saving – capturing the access–transaction–accumulation gradient of household digital-finance maturity; the supply block comprises the six GARI pillars. The dependent variable is account ownership in the panel and the demand sub-index in the cross-section. The controls capture the standard macro determinants of financial development: income, connectivity, urbanization, institutional quality, financial depth, and human capital.

2.3. Construction of the ABRI

The ABRI is built by two-stage principal-component analysis (PCA). Within each block, indicators are first standardized (Eq. 1), where x_{ik} is the raw value of indicator k for economy i, z_{ik} its standardized value, and μ_k and σ_k its sample mean and standard deviation.

$$z_{ik} = \frac{x_{ik} - \mu_k}{\sigma_k}. \tag{1}$$

Each sub-index is the score on the first principal component of its block (Eq. 2): the demand sub-index from the three Findex indicators and the supply sub-index from the six GARI pillars. The score F_i loads the standardized indicators with weights l_k, the elements of the eigenvector of the block's correlation matrix R that corresponds to its largest eigenvalue λ_1.

$$F_i = \sum_k l_k z_{ik}. \tag{2}$$

Each component score is linearly rescaled to the 0-100 range (Eq. 3), where F_i is the component score, F_{min} and F_{max} its sample minimum and maximum, and I_i the resulting 0-100 index; this yields the demand sub-index D_i and the supply sub-index S_i.

$$I_i = 100 \cdot \frac{F_i - F_{\min}}{F_{\max} - F_{\min}}. \tag{3}$$

The integral ABRI repeats the same logic on the two sub-indices (Eq. 4): the integral score A_i is the first principal component of the standardized demand and supply sub-indices, with PCA weights m_1 and m_2 and z(·) the standardization of Eq. 1; A_i is then rescaled to 0-100 by Eq. 3 to give the ABRI.

$$A_i = m_1 \, z(D_i) + m_2 \, z(S_i). \tag{4}$$

The adequacy of the single-factor representation is assessed with three standard diagnostics, reported in Table 2. Bartlett's test of sphericity (Eq. 5) tests whether the correlation matrix departs from the identity matrix, where χ^2 is the test statistic, n the sample size, p the number of indicators, |R| the determinant of the correlation matrix, and *df* the degrees of freedom.

$$\chi^2 = -\left[n - 1 - \frac{2p+5}{6}\right] \cdot \ln|R|, \quad df = \frac{p(p-1)}{2}. \tag{5}$$

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy compares zero-order with partial correlations (Eq. 6), where r_{ij} are pairwise correlations and a_{ij} the corresponding partial (anti-image) correlations; values above 0.6 are acceptable.

$$KMO = \frac{\Sigma\Sigma r_{ij}^2}{\Sigma\Sigma r_{ij}^2 + \Sigma\Sigma a_{ij}^2}, \quad i \neq j \tag{6}$$

Internal consistency is summarized by Cronbach's α (Eq. 7), where k is the number of items, σ_i^2 the item variances, and the denominator the variance of their sum.

$$\alpha = \left[\frac{k}{k-1}\right] \cdot \left(1 - \frac{\sum_i \sigma_i^2}{\sigma_T^2}\right). \tag{7}$$

Construct validity is examined by correlating the supply sub-index with the published GARI score and the PCA index with its equal-weight counterpart; robustness is checked by alternative weighting, indicator substitution, and leave-one-pillar-out re-estimation (reported in Appendix D).

2.4. Empirical strategy

Country typology. To group economies by readiness without imposing thresholds, k-means clustering is applied to the two standardized sub-indices, minimizing the within-cluster sum of squares (Eq. 8), where z_i is the standardized (demand, supply) vector for economy i and the μ-terms are the centroids of clusters c (which form the set C), and ‖·‖ is the Euclidean norm.

$$\min \sum_c \sum_{i \in C_c} \| z_i - \mu_c \|^2. \tag{8}$$

The number of clusters is chosen by maximizing the average silhouette width (Eq. 9), where a_i is the mean within-cluster distance and b_i the mean distance to the nearest other cluster; the criterion favors $k = 2$. Independently, economies are cross-classified into a 2 × 2 strategic matrix by comparing each sub-index with its sample median, distinguishing integrated leaders, demand-led, supply-led, and nascent profiles.

$$s_i = \frac{b_i - a_i}{\max(a_i, b_i)}. \tag{9}$$

Cross-sectional nexus. The association between AI readiness and demand-side maturity is estimated by OLS with the demand sub-index D_i as the dependent variable (Eq. 10), where G_i is the GARI overall score and X_{ji} the controls, β_0 the intercept, β_1 and γ_j the slope coefficients, and ε_i the error term. Standard errors are heteroskedasticity-robust (HC3); standardized coefficients are reported for comparability, and variance-inflation factors gauge multicollinearity.

$$D_i = \beta_0 + \beta_1 G_i + \sum_j \gamma_j X_{ji} + \varepsilon_i. \tag{10}$$

Panel dynamics. To test whether the relationship holds within countries over time, account ownership y_{it} is modeled with two-way (country and wave) fixed effects (Eq. 11), where α_i are country effects, δ_t wave effects, x_{it} = (internet, log GDP, mobile, urban, regulatory quality)′, and E_{it} the EGDI proxy (the θ term, included in Models 2-3), β is the coefficient vector on x_{it}, and ε_{it} the error term; standard errors are clustered by country. EGDI is examined both alongside and in place of internet penetration to identify the channel through which state capacity operates.

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$$y_{it} = \alpha_i + \delta_t + \beta' x_{it} + \theta E_{it} + \varepsilon_{it}. \quad (11)$$

Finally, an AI-specific specification interacts the GARI score G_i with a centered wave trend τ_t, with a base-GDP × trend term (g_i = base-year log GDP per capita) absorbing income convergence (Eq. 12), where φ and ψ are the coefficients on the $G_i \times \tau_t$ and $g_i \times \tau_t$ interactions, respectively; the main effects of G_i and g_i are absorbed by the country fixed effects, so only their interactions with the trend are identified.

$$y_{it} = \alpha_i + \delta_t + \varphi(G_i \cdot \tau_t) + \psi(g_i \cdot \tau_t) + \beta' x_{it} + \varepsilon_{it}. \quad (12)$$

2.5. Limitations

Several limitations qualify the findings. First, the GARI is a single 2025 cross-section, so AI readiness cannot be identified within the panel; the EGDI proxy and GARI × trend term mitigate but do not fully resolve this. Second, the Findex waves are irregular and survey-based, the panel unbalanced, and the cross-sectional estimates associational rather than causal. Third, the sample skews toward middle- and high-income economies, limiting external validity for data-poor countries. Fourth, the self-reported mobile/internet-banking indicator was dropped for correlating negatively with the access–payment–saving core, leaving one behavioral channel outside the index. Fifth, the PCA weights are sample-estimated, so the index is relative rather than absolute. Sixth, the ABRI captures the country-level enabling environment rather than the tangible deployment of AI by financial institutions. Within this framework, readiness constitutes a prerequisite for, rather than empirical proof of, AI-driven banking; bridging this gap would necessitate bank-level adoption data. Finally, because the infrastructure channel detailed in Section 3.6 relies on coefficient shifts across specifications, it provides suggestive evidence of an underlying mechanism rather than constituting a formal mediation analysis.

3. RESULTS AND DISCUSSION

3.1. Sample and descriptive statistics

The estimation sample comprises the 97 economies observed in both the demand-side and supply-side sources – the intersection of the 2024 Global Findex wave (with non-missing digital-finance indicators) and the 2025 Government AI Readiness Index (GARI); one economy (Kosovo) is lost to missing Findex coverage. Table 1 reports the distribution of the three demand indicators, the six GARI pillars, and the three composite indices.

Demand-side penetration is low and widely dispersed. On average, 46% of adults hold a digitally enabled account, 29% made or received a digital payment, and only 19% save formally at a financial institution; the descending means trace a familiar

Table 1. Descriptive statistics (N = 97)

Variable	Mean	SD	Min	Median	Max
Demand indicators ***(share of adults, 0-1)***					
Digitally enabled account ownership	0.46	0.22	0.07	0.48	0.96
Made or received a digital payment	0.29	0.21	0.02	0.24	0.73
Saved formally (at a financial institution)	0.19	0.12	0.03	0.17	0.67
GARI pillars ***(0-100)***					
Policy Capacity	43.96	29.95	0.00	35.00	100.00
AI Infrastructure	41.69	11.67	18.43	41.12	78.36
Governance	55.05	18.94	3.50	56.63	93.21
Public Sector Adoption	48.20	23.90	2.09	48.35	94.78
Development & Diffusion	28.57	12.80	9.19	27.94	74.67
Resilience	40.58	13.67	13.85	38.04	77.34
Composite indices ***(0-100)***					
Demand sub-index	37.70	22.57	0.00	32.11	100.00
Supply sub-index	42.12	22.62	0.00	40.74	100.00
ABRI (integral)	38.45	21.05	0.00	34.50	100.00

Note: Demand indicators are population shares (World Bank Global Findex 2024 wave); GARI pillars and composite indices are scaled 0-100. Composite indices are PCA-derived (see Section 3.2).

adoption gradient running from access through transaction to accumulation. Supply-side capacity is higher on average but uneven in composition: Governance is the strongest pillar (mean 55.05) and Development & Diffusion the weakest (28.57), while AI Infrastructure has the most compressed distribution (SD 11.67) and Policy Capacity the widest (SD 29.95). On the common 0-100 scale, the supply sub-index (mean 42.12) modestly exceeds the demand sub-index (37.70), and the integral ABRI averages 38.45.

3.2. ABRI construction and validation

The ABRI aggregates two principal-component sub-indices. The demand sub-index is the first principal component (PC1) of the three Findex indicators; the supply sub-index is PC1 of the six GARI pillars; the integral index is PC1 of the two sub-indices. Each block is standardized before extraction, oriented so that higher values denote greater readiness, and rescaled to 0-100. Table 2 reports the loadings, the share of variance explained, and the factor-adequacy statistics.

Both blocks are well represented by a single factor. For the demand block, Bartlett's test of sphericity rejects the identity-correlation null ($\chi^2 = 111.7$, df = 3, $p \approx 4.7 \times 10^{-24}$), the Kaiser-Meyer-Olkin measure is 0.696, and Cronbach's α is 0.791; PC1 accounts for 74.4% of the variance with near-equal loadings (0.541, 0.593, 0.596), indicating a balanced composite rather than one dominated by a single item. The supply block is stronger: Bartlett $\chi^2 = 438.9$ (df = 15, $p \approx 4.5 \times 10^{-84}$), KMO 0.849, α 0.894, with PC1 explaining 73.4% of the variance and all six pillars loading evenly (0.383-0.430). In both blocks, the variance is concentrated in the leading component (demand 0.744 versus 0.163 for the second; supply 0.734 versus 0.083), and only the first component has an eigenvalue above unity under the Kaiser criterion.

The composite is robust to construction choices. The PCA-weighted integral index is effectively identical to a simple equal-weight average of the two sub-indices (r = 1.0), and the supply sub-index reproduces the published GARI overall score almost exactly (r = 0.997). The index is also invariant to indicator selection: equal weighting leaves the ranking unchanged (Spearman ρ = 1.000), substituting account ownership for the three-indicator demand block preserves it (ρ = 0.975), and dropping any single GARI pillar changes it negligibly (minimum ρ = 0.996); these checks are reported in full in Appendix D. These near-equivalences

Table 2. ABRI construction and factor-adequacy diagnostics

Panel A. Demand sub-index (Findex 2024) – indicator		PC1 loading
Digitally enabled account ownership		0.541
Made or received a digital payment		0.593
Saved formally (financial institution)		0.596
Variance explained by PC1		74.4%
Panel B. Supply sub-index (GARI 2025, six pillars) – pillar		PC1 loading
Policy Capacity		0.421
AI Infrastructure		0.416
Governance		0.413
Public Sector Adoption		0.383
Development & Diffusion		0.430
Resilience		0.384
Variance explained by PC1		73.4%
Panel C. Factor adequacy	**Demand**	**Supply**
Bartlett χ^2 (df)	111.7 (3)	438.9 (15)
Bartlett p	$\approx 4.7 \times 10^{-24}$	$\approx 4.5 \times 10^{-84}$
Kaiser-Meyer-Olkin	0.696	0.849
Cronbach α	0.791	0.894
First-component variance share	0.744	0.734
Second-component variance share	0.163	0.083

Note: Loadings are PC1 coefficients on standardized inputs. Validation: integral ABRI vs. equal-weight average r = 1.0; supply sub-index vs. GARI overall r = 0.997; demand–supply r = 0.655; Spearman (ABRI, GARI overall) = 0.904. Robustness checks (aggregation, indicator substitution, and leave-one-pillar-out) are in Appendix D.

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are informative rather than problematic. PCA serves here as a validation device rather than as a source of non-trivial weights, establishing that each block is well represented by a single latent dimension and that the weights are not an artefact of the aggregation choice. The contribution of the ABRI accordingly lies in integrating demand- and supply-side measurement within one instrument rather than in the weighting scheme. The fact that a fully transparent equal-weight version reproduces the ranking exactly further strengthens replicability. Importantly, the ABRI is not redundant with AI readiness alone – its rank correlation with the GARI overall score is high but well below unity (Spearman ρ = 0.904), so the demand dimension reorders roughly a tenth of the ranking. The two sub-indices are only moderately correlated (r = 0.655), leaving substantial cross-country heterogeneity that motivates the typology in Sections 3.3 and 3.4. One candidate demand indicator – self-reported use of mobile or internet banking – was excluded from the composite because it correlates negatively with the otherwise coherent access-payment-saving block; this "card-first versus internet-first" divergence is a reminder that digital-finance maturity is not a single pathway, which bounds any composite built from it.

3.3. Readiness landscape: country clusters

To characterize the readiness landscape without imposing thresholds, k-means clustering was applied to the standardized demand and supply sub-indices (20 initializations, fixed seed). The average silhouette width is maximized at k = 2 (0.476), yielding two well-separated groups (Table 3, Panel A). The first cluster – advanced adopters (n = 42) – combines high demand (56.2) and high supply (62.5) for a mean ABRI of 58.3; the second – nascent markets (n = 55) – is uniformly low (demand 23.6, supply 26.6, ABRI 23.3). The partition runs along the diagonal of overall development rather than separating demand-leaders from supply-leaders, consistent with the moderate demand–supply correlation documented above.

As the illustrative application described in Section 2.1, Table 3 (Panel B) locates the six economies of the regional group. Azerbaijan (ABRI 47.5, rank 31 of 97) falls among the advanced adopters, but its profile is internally asymmetric: supply capacity (59.2) substantially exceeds demand maturity (38.3), so household adoption – not state AI readiness – is the binding frontier. Uzbekistan (48.0, rank 29) shows the same supply-ahead pattern, whereas Georgia (45.4, rank 34) is the mirror case, with demand modestly ahead of supply. Kazakhstan (65.7, rank 12) and Türkiye (63.8, rank 14) are the most balanced and highest-placed regional economies, while Armenia (34.5, rank 49) records the lowest readiness of the group and is its only member of the nascent-markets cluster.

3.4. Strategic positioning matrix

Clustering by development level masks strategically important asymmetries. To expose them, economies were cross-classified against the sample medians of the two sub-indices (demand 32.1,

Table 3. Cluster profiles and selected economies (k-means, k = 2)

Panel A. Cluster				
Cluster	**n**	**Demand**	**Supply**	**ABRI**
Advanced adopters	42	56.2	62.5	58.3
Nascent markets	55	23.6	26.6	23.3

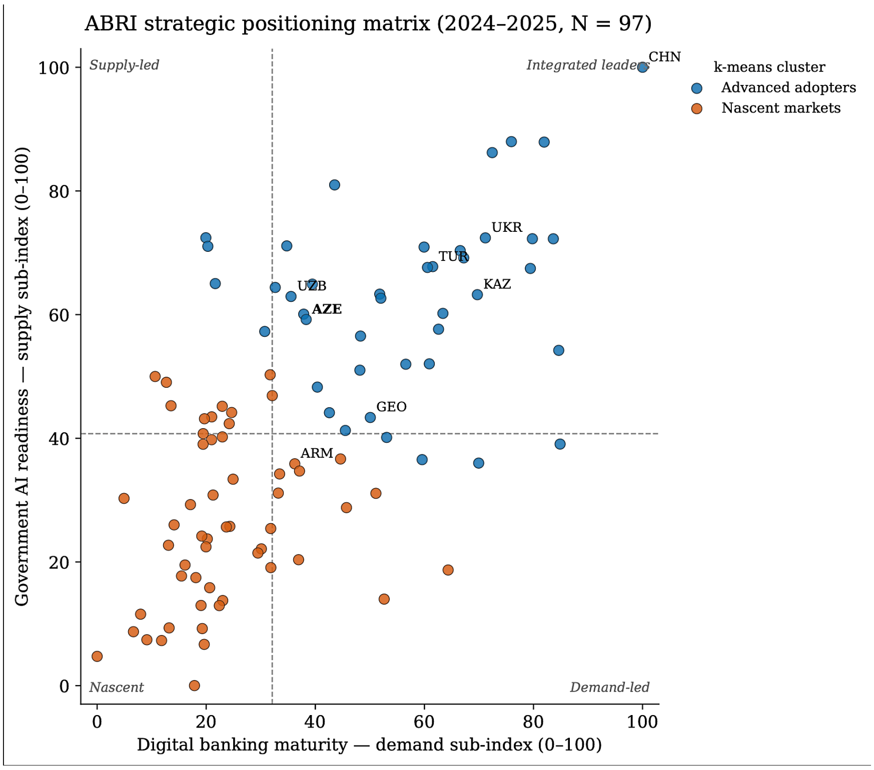
Panel B. Economy					
Country	**Demand**	**Supply**	**ABRI**	**Rank**	**Cluster**
Kazakhstan	69.7	63.2	65.7	12	Advanced
Türkiye	61.5	67.8	63.8	14	Advanced
Uzbekistan	35.5	62.9	48.0	29	Advanced
Azerbaijan	38.3	59.2	47.5	31	Advanced
Georgia	50.1	43.4	45.4	34	Advanced
Armenia	36.2	35.9	34.5	49	Nascent

Note: Clustering on standardized demand and supply sub-indices; silhouette maximized at k = 2 (0.476). "Advanced" / "Nascent" in Panel B denote the advanced-adopters and nascent-markets clusters. Azerbaijan (bold) is an advanced adopter. Panel B is ordered by ABRI rank.

supply 40.7), producing the 2 × 2 matrix in Figure 1. Thirty-five economies are Integrated leaders (high on both), and 34 are Nascent (low on both), so roughly 71% lie on the alignment diagonal. The remaining 28 split evenly: 14 Supply-led economies (low demand, high supply) – including the Philippines, Egypt, Jordan, Moldova, Mexico, Pakistan, Bangladesh, and Morocco – and 14 Demand-led economies (high demand, low supply) – including Mongolia, North Macedonia, Venezuela, Namibia, Montenegro, Belize, Bosnia and Herzegovina, and Kyrgyzstan.

The reordering relative to GARI makes the demand contribution concrete. Incorporating demand lifts demand-led economies sharply in the ABRI ranking – Venezuela by 39 places, North Macedonia and Belize by 33, Mongolia by 32, Namibia by 26, and Croatia by 22 – while supply-led economies fall once weak household adoption is accounted for: Bangladesh by 28, the Philippines by 26, Egypt and Pakistan by 24, Morocco by 22, and Lebanon by 21. At the top of the index, China leads (100), followed by Poland (84.6), Saudi Arabia (81.5), Brazil (78.8), and Thailand (77.4), with Ukraine eighth (71.1). Azerbaijan sits in the high/high quadrant – above both medians – yet its internal supply-over-demand gap identifies the demand side as its policy frontier.

Taken together, the index-level evidence is descriptive: demand-side and supply-side readiness are related but distinct dimensions, and almost a third of economies lead on one side only. That economies cluster by development rather than by demand- versus supply-leadership echoes latent structures in cross-country digital transformation (Pakhnenko et al., 2025); yet off-diagonal cases – and supply-ahead profiles such as Azerbaijan – suggest that the binding frontier often lies on the demand side, which a supply-only index would miss. Because readiness for personalized, AI-driven banking depends on household uptake, the micro-evidence that adoption hinges on usefulness, ease of use, and trust (Hedau, 2025) – and that AI quality and trust predict the intention to



Note: Economies are plotted by their demand and supply sub-indices; dashed lines mark the sample medians (demand 32.1, supply 40.7). Quadrants: Integrated leaders (high demand, high supply), Demand-led (high demand, low supply), Supply-led (low demand, high supply), and Nascent (low demand, low supply). Marker color denotes the k-means cluster (advanced adopters vs. nascent markets); Azerbaijan is highlighted.

Figure 1. ABRI strategic positioning matrix (2024–2025, N = 97)

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use robo-advisory services despite a preference for human fallback (Piotrowski & Orzeszko, 2023) – implies that supply-side capacity translates into uptake only where household trust and usability are secured.

3.5. The demand-supply nexus

The analysis now turns from description to estimation, asking whether national AI readiness is associated with demand-side digital-finance maturity once standard development controls are held fixed. Table 4 reports cross-sectional OLS regressions with HC3-robust standard errors (N = 93; four economies are lost to missing controls), using the demand sub-index as the dependent variable.

Model 1 includes only the controls – log GDP per capita, internet use, regulatory quality, domestic credit, and tertiary enrollment – and explains 55.6% of the variance; income is the dominant correlate (12.437, $p = 0.008$) and tertiary enrollment is marginal (0.201, $p = 0.078$), with the remaining controls insignificant. Adding the GARI overall score (Model 2) raises the fit to 59.6% ($\Delta R^2 = 0.039$); the coefficient is positive and significant (0.451, SE 0.189, $z = 2.39$, $p = 0.017$), income remains significant (10.520, $p = 0.029$), and regulatory quality is fully displaced. In standardized terms, income remains the strongest predictor ($\beta = 0.441$, $p = 0.029$) and AI readiness the second largest and significant ($\beta = 0.299$, $p = 0.017$); the remaining controls – tertiary enrollment (0.158), domestic credit (0.141), internet use (–0.199), and regulatory quality (0.079) – are individually insignificant once income and AI readiness are present. Multicollinearity is not a concern – all variance-inflation factors are below 10 (maximum 6.26 for income; 2.28 for the GARI score); the full correlation matrix is reported in Appendix C. Conditional on development, then, more AI-ready states exhibit deeper household digital-finance adoption.

The cross-sectional evidence is associational rather than causal, but it extends to the demand side the evidence linking AI readiness to banking-sector performance (Sitnicka et al., 2025) and is consistent with the conditional, uneven view of AI and FinTech effects (Siminică et al., 2025). Demand and supply readiness appear distinct rather than interchangeable – AI readiness alone does not fully capture household adoption – which motivates a two-sided index rather than a supply-only ranking.

3.6. Financial-inclusion dynamics

The cross-section cannot establish whether this association reflects a within-country dynamic. Table 5 therefore estimates two-way (country and wave) fixed-effects models of account ownership across the five Findex waves, with standard errors clustered by country (648 complete observations; nine singleton country effects are dropped, leaving an estimation sample of 639 observations across 142 countries with two or more waves; see Table B1, Appendix B). Because the GARI score is cross-sectional and time-invariant, the biennial E-Government Development Index (EGDI) serves as the time-varying proxy for state digital capacity; the two supply measures are strongly convergent

Table 4. Cross-sectional determinants of demand-side digital maturity

Regressor	M1 coef. (SE)	M2 coef. (SE)	M2 std. β	VIF
GARI overall	–	0.451** (0.189)	0.299**	2.28
Log GDP per capita	12.437*** (4.666)	10.520** (4.821)	0.441**	6.26
Internet use	−0.195 (0.176)	−0.178 (0.177)	−0.199	5.60
Tertiary enrollment	0.201* (0.114)	0.131 (0.118)	0.158	3.16
Domestic credit	0.138 (0.110)	0.099 (0.092)	0.141	1.42
Regulatory quality	5.660 (4.155)	2.823 (4.367)	0.079	1.78
Constant	–76.968* (35.834)	–76.017* (36.858)		
R^2	0.556	0.596		
ΔR^2 (M2-M1)		0.039		
N	93	93		

Note: DV = demand sub-index. OLS with HC3-robust SE in parentheses. Standardized β and VIF are from Model 2; standardized betas carry the same significance as the corresponding unstandardized coefficients (standardization only rescales the variables). Significance: *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 5. Panel fixed-effects estimates of account ownership

Regressor	M1 (baseline)	M2 (+ EGDI)	M3 (– internet)
Internet use	0.310***	0.283***	–
EGDI	–	12.36 (8.45)	27.09*** (8.34)
Log GDP per capita	9.484**	Included	Included
Mobile subscriptions	0.054*	Included	Included
Urban population	n.s.	Included	Included
Regulatory quality	n.s.	Included	Included
Country fixed effects	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes
Observations (FE sample)	≈ 639	≈ 639	≈ 639

Note: DV = account ownership (% of adults). Two-way fixed effects (country, wave); SE clustered by country in parentheses. The FE estimation sample is 639 observations (142 countries, 5 waves) after dropping nine singleton country effects from 648 complete cases. EGDI = E-Government Development Index (time-varying supply proxy). "Included" denotes a control retained in the model whose coefficient is omitted here for brevity. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; n.s. = not significant.

(Pearson $r = 0.821$, Spearman $\rho = 0.823$ against the 2024 GARI overall, N = 96), which validates the substitution.

In the baseline (Model 1), internet penetration is the dominant driver of account ownership (0.310, $p < 0.001$), with income (9.484, $p = 0.041$) and mobile subscriptions (0.054, $p = 0.093$) also contributing. Adding EGDI (Model 2) leaves it insignificant (12.36, SE 8.45, $p = 0.146$) while internet remains strong (0.283, $p = 0.001$). When internet is removed (Model 3), however, EGDI turns large and significant (27.09, SE 8.34, $p = 0.001$). The e-government coefficient is insignificant alongside internet penetration yet large and significant once internet is excluded. This pattern is consistent with an infrastructure-mediated channel. Within countries, the growth of account ownership appears infrastructure-driven, with state digital capacity operating upstream of the connectivity that households use. Two caveats bound this reading. First, it is suggestive channel evidence derived from the behavior of coefficients across specifications, not a formal mediation test, because no decomposition of direct and indirect effects is estimated. Second, it concerns e-government capacity in general rather than AI readiness specifically.

A final, AI-specific check asks whether more AI-ready economies expanded inclusion faster over time. Interacting the GARI score with a centered wave trend on the GARI sub-sample (N = 423, 94 countries) yields a null effect on its own (GARI × trend = –0.004, $p = 0.90$). Once a base-GDP × trend term is added to absorb income convergence, the interaction becomes positive and significant (GARI × trend = 0.088, $p = 0.041$) alongside a strong convergence effect (base GDP × trend = –2.442, $p = 0.001$). Net of income convergence, AI-readier economies digitalized financial access more rapidly – though the sensitivity of this term to the convergence control means it is best read as suggestive rather than decisive.

Read against the literature, the panel pattern is consistent with state capacity working through the digital infrastructure households use – accelerating infrastructure rollout (Lyeonov et al., 2025), with connectivity and mobile ownership as prerequisites for inclusion (Klapper et al., 2025) – while the AI-specific signal, the positive GARI × trend interaction net of income convergence, remains tentative and control-sensitive.

CONCLUSION

This study gauged how prepared national banking systems are – at the level of the country's enabling environment – for the shift from mobile applications to AI-driven, personalized services by joining demand and supply in one composite. Using the World Bank Global Findex (2011–2024) and the Government AI Readiness Index 2025 for 97 economies, the AI-Banking Readiness Index (ABRI) was built by two-stage PCA and examined through clustering, a demand–supply matrix, and cross-sectional and panel fixed-effects regressions.

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Four findings stand out. Demand and supply readiness are only moderately aligned (r = 0.655), and adding the demand dimension reorders about a tenth of the AI-readiness ranking (ρ = 0.904 against GARI), splitting economies into advanced adopters, nascent markets, and 28 one-sided leaders. Across countries, AI readiness is positively associated with deeper household digital-finance adoption once income is controlled (β = 0.451, p = 0.017; ΔR^2 = 3.9 pp). Within countries, the pattern is consistent with e-government capacity supporting account ownership through digital infrastructure. The e-government proxy is insignificant alongside internet penetration (12.36, p = 0.146) but large once it replaces it (27.09, p = 0.001), a contrast read as suggestive channel evidence rather than a formal mediation result. Azerbaijan typifies its region – an advanced adopter (ABRI 47.5, rank 31) whose supply (59.2) exceeds demand (38.3), so its binding constraint is on the household side.

These results imply opposite priorities for the two faces of unreadiness. Where AI capacity outpaces adoption – the supply-led group and supply-ahead cases such as Azerbaijan and Uzbekistan – the task is to convert state capacity into everyday use via infrastructure: interoperable instant payments, digital-identity-linked accounts, merchant incentives, and literacy programs. Where adoption is high but readiness lags, the reverse is needed – data-protection and AI-governance frameworks, supervisory capacity, and public-sector AI skills – so an engaged customer base can absorb AI-driven personalization without amplifying exclusion or model risk.

More broadly, because demand and supply diverge for almost a third of countries, the ABRI gives regulators, central banks, and development institutions a diagnostic for targeting the binding constraint rather than treating readiness as one dimension; for Azerbaijan and its peers, closing the demand gap would turn already-strong AI readiness into genuinely AI-enabled banking.

AUTHOR CONTRIBUTIONS

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Visualization: Leyla Huseynova, Rauf Salayev.
Writing – original draft: Mehriban Aliyeva, Leyla Huseynova, Rauf Salayev.
Writing – reviewing & editing: Sevinj Abbasova, Tetiana Vasylieva, Esmira Ahmadova.

DATA AVAILABILITY

All data analyzed in this study are publicly available from their original providers. The demand-side indicators are drawn from the Global Findex Database 2025 (Klapper et al., 2025), and the supply-side indicators from the Government AI Readiness Index 2025 (Oxford Insights, 2025). Macroeconomic and infrastructure controls are obtained from the World Development Indicators (World Bank, 2025) and the Worldwide Governance Indicators (World Bank, 2024); the e-government proxy is the United Nations E-Government Development Index (United Nations, 2024).

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APPENDIX A

Table A1. Variables, definitions, and sources

Variable	Definition and units	Source
Dependent variables		
Account ownership	Adults (15+) with an account at a financial institution or mobile-money provider (%)	Global Findex 2025
Demand sub-index	PCA composite of the three demand indicators, rescaled 0-100	Authors' computation
Demand-side indicators (Findex, 2024 wave)		
Digitally enabled account	Adults with a digitally enabled account (share of adults)	Global Findex 2025
Digital payment	Adults who made or received a digital payment (share)	Global Findex 2025
Formal saving	Adults who saved at a financial institution (share)	Global Findex 2025
Supply-side measures		
GARI overall	Government AI Readiness overall score (0-100)	Oxford Insights GARI 2025
GARI pillars (×6)	Policy Capacity; AI Infrastructure; Governance; Public Sector Adoption; Development & Diffusion; Resilience (0-100 each)	Oxford Insights GARI 2025
EGDI	UN E-Government Development Index; time-varying panel supply proxy (0-1)	UN E-Government Survey
Controls		
Log GDP per capita	Natural log of GDP per capita, constant US$	WDI
Internet use	Individuals using the internet (% of population)	ITU / WDI
Mobile subscriptions	Mobile-cellular subscriptions per 100 people	ITU / WDI
Urban population	Urban population (% of total)	WDI
Regulatory quality	WGI regulatory-quality estimate	WGI
Domestic credit	Domestic credit to private sector (% of GDP)	WDI
Tertiary enrollment	Gross tertiary-education enrollment ratio (%)	WDI

Note: WDI = World Development Indicators; WGI = Worldwide Governance Indicators; ITU = International Telecommunication Union. Findex indicators are population shares; composite indices are author-computed (Section 2.3). The panel uses all five Findex waves (2011–2024); the cross-section uses the 2024 wave matched to GARI 2025.

APPENDIX B. Analytical samples and economies

Table B1. Analytical samples by stage of the analysis

Panel A. Analytical samples overview

Analytical stage	Data requirements	Countries	Observations	Relation to the ABRI sample (N = 97)
ABRI construction and typology (Sections 3.1-3.4)	Intersection of the 2024 Findex digital-finance indicators and the 2025 GARI	97	97	Reference sample
Cross-sectional regressions (Section 3.5)	ABRI sample with complete WDI/WGI controls	93	93	Subset: four economies lost to missing controls
Panel fixed effects (Section 3.6)	Account ownership (Findex waves 2011–2024), EGDI, WDI/WGI controls; ≥ 2 complete waves	142	639	Nests 91 of the 97 economies; adds 51 economies with incomplete ABRI inputs
GARI × trend specification (Section 3.6)	Panel sample restricted to GARI coverage	94	423	Panel subsample of GARI-covered economies

Note: The six ABRI economies absent from the fixed-effects panel (observed in fewer than two complete Findex waves) are Belize, Libya, Mongolia, Namibia, Venezuela, and West Bank and Gaza. See Section 2.1.

Panel B. Economies in the ABRI sample (N = 97)

The table lists the 97 economies in the ABRI sample, with their World Bank income group, integral ABRI score, ABRI rank, k-means cluster, and strategic-matrix quadrant. Economies are ordered by ABRI rank.

Table B2. Economies in the ABRI sample (N = 97): income group, ABRI score, rank, cluster, and quadrant

Rank	ISO3	Economy	Income group	ABRI	Cluster	Quadrant
1	CHN	China	Upper middle income	100.0	Advanced	Integrated leaders
2	POL	Poland	High income	84.6	Advanced	Integrated leaders
3	SAU	Saudi Arabia	High income	81.5	Advanced	Integrated leaders
4	BRA	Brazil	Upper middle income	78.8	Advanced	Integrated leaders
5	THA	Thailand	Upper middle income	77.4	Advanced	Integrated leaders
6	MYS	Malaysia	Upper middle income	75.5	Advanced	Integrated leaders
7	BGR	Bulgaria	Upper middle income	72.8	Advanced	Integrated leaders
8	UKR	Ukraine	Lower middle income	71.1	Advanced	Integrated leaders
9	HRV	Croatia	High income	68.7	Advanced	Integrated leaders
10	SRB	Serbia	Upper middle income	67.7	Advanced	Integrated leaders
11	VNM	Viet Nam	Lower middle income	67.4	Advanced	Integrated leaders
12	KAZ	Kazakhstan	Upper middle income	65.7	Advanced	Integrated leaders
13	ARG	Argentina	Upper middle income	64.6	Advanced	Integrated leaders
14	TUR	Turkiye	Upper middle income	63.8	Advanced	Integrated leaders
15	ROU	Romania	High income	63.2	Advanced	Integrated leaders
16	IND	India	Lower middle income	61.3	Advanced	Integrated leaders
17	MNG	Mongolia	Lower middle income	61.1	Advanced	Demand-led
18	ZAF	South Africa	Upper middle income	60.9	Advanced	Integrated leaders
19	MUS	Mauritius	Upper middle income	59.2	Advanced	Integrated leaders
20	OMN	Oman	High income	56.5	Advanced	Integrated leaders
21	KEN	Kenya	Lower middle income	56.3	Advanced	Integrated leaders
22	CRI	Costa Rica	Upper middle income	55.4	Advanced	Integrated leaders
23	IRN	Iran, Islamic Rep.	Lower middle income	53.2	Advanced	Integrated leaders
24	MKD	North Macedonia	Upper middle income	51.8	Advanced	Demand-led
25	IDN	Indonesia	Lower middle income	51.8	Advanced	Integrated leaders
26	NGA	Nigeria	Lower middle income	51.3	Advanced	Integrated leaders
27	PER	Peru	Upper middle income	51.0	Advanced	Integrated leaders
28	GHA	Ghana	Lower middle income	48.4	Advanced	Integrated leaders
29	UZB	Uzbekistan	Lower middle income	48.0	Advanced	Integrated leaders
30	ECU	Ecuador	Upper middle income	47.7	Advanced	Integrated leaders
31	AZE	Azerbaijan	Upper middle income	47.5	Advanced	Integrated leaders
32	COL	Colombia	Upper middle income	47.3	Advanced	Integrated leaders
33	NAM	Namibia	Upper middle income	46.8	Advanced	Demand-led
34	GEO	Georgia	Upper middle income	45.4	Advanced	Integrated leaders
35	MNE	Montenegro	Upper middle income	45.3	Advanced	Demand-led
36	PHL	Philippines	Lower middle income	44.8	Advanced	Supply-led
37	EGY	Egypt, Arab Rep.	Lower middle income	44.3	Advanced	Supply-led
38	LKA	Sri Lanka	Lower middle income	43.0	Advanced	Integrated leaders
39	MDA	Moldova	Upper middle income	42.6	Advanced	Supply-led
40	SEN	Senegal	Lower middle income	42.0	Advanced	Integrated leaders
41	DOM	Dominican Republic	Upper middle income	42.0	Advanced	Integrated leaders
42	JOR	Jordan	Upper middle income	41.9	Advanced	Supply-led
43	VEN	Venezuela, RB	Upper middle income	40.1	Nascent	Demand-led
44	BIH	Bosnia and Herzegovina	Upper middle income	39.7	Nascent	Demand-led
45	MEX	Mexico	Upper middle income	39.6	Nascent	Supply-led
46	PAN	Panama	High income	39.2	Nascent	Demand-led
47	ZMB	Zambia	Low income	38.0	Nascent	Integrated leaders

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Table B2 (cont.). Economies in the ABRI sample (N = 97): income group, ABRI score, rank, cluster, and quadrant

Rank	ISO3	Economy	Income group	ABRI	Cluster	Quadrant
48	KGZ	Kyrgyz Republic	Lower middle income	35.7	Nascent	Demand-led
49	ARM	Armenia	Upper middle income	34.5	Nascent	Demand-led
50	BWA	Botswana	Upper middle income	34.3	Nascent	Demand-led
51	ALB	Albania	Upper middle income	32.8	Nascent	Supply-led
52	CIV	Cote d'Ivoire	Lower middle income	32.4	Nascent	Supply-led
53	PRY	Paraguay	Upper middle income	32.2	Nascent	Demand-led
54	BLZ	Belize	Upper middle income	31.7	Nascent	Demand-led
55	TUN	Tunisia	Lower middle income	31.7	Nascent	Supply-led
56	ETH	Ethiopia	Low income	30.6	Nascent	Supply-led
57	UGA	Uganda	Low income	30.5	Nascent	Demand-led
58	TZA	Tanzania	Lower middle income	29.9	Nascent	Nascent
59	DZA	Algeria	Lower middle income	29.7	Nascent	Supply-led
60	BGD	Bangladesh	Lower middle income	29.2	Nascent	Supply-led
61	NPL	Nepal	Lower middle income	28.7	Nascent	Nascent
62	PAK	Pakistan	Lower middle income	28.6	Nascent	Supply-led
63	BEN	Benin	Lower middle income	28.4	Nascent	Supply-led
64	MAR	Morocco	Lower middle income	27.7	Nascent	Supply-led
65	SLV	El Salvador	Lower middle income	27.5	Nascent	Nascent
66	CMR	Cameroon	Lower middle income	27.4	Nascent	Nascent
67	SWZ	Eswatini	Lower middle income	26.9	Nascent	Demand-led
68	TGO	Togo	Low income	26.9	Nascent	Nascent
69	GAB	Gabon	Upper middle income	24.3	Nascent	Nascent
70	KHM	Cambodia	Lower middle income	24.2	Nascent	Nascent
71	BOL	Bolivia	Lower middle income	23.7	Nascent	Nascent
72	LSO	Lesotho	Lower middle income	23.7	Nascent	Nascent
73	LBY	Libya	Upper middle income	23.2	Nascent	Nascent
74	LAO	Lao PDR	Lower middle income	22.8	Nascent	Nascent
75	PSE	West Bank and Gaza	Lower middle income	21.3	Nascent	Nascent
76	ZWE	Zimbabwe	Lower middle income	20.1	Nascent	Nascent
77	TJK	Tajikistan	Lower middle income	19.8	Nascent	Nascent
78	BFA	Burkina Faso	Low income	19.3	Nascent	Nascent
79	IRQ	Iraq	Upper middle income	18.1	Nascent	Nascent
80	MOZ	Mozambique	Low income	16.4	Nascent	Nascent
81	GMB	Gambia, The	Low income	16.3	Nascent	Nascent
82	GTM	Guatemala	Upper middle income	15.9	Nascent	Nascent
83	MRT	Mauritania	Lower middle income	15.8	Nascent	Nascent
84	MWI	Malawi	Low income	15.8	Nascent	Nascent
85	MLI	Mali	Low income	15.7	Nascent	Nascent
86	LBN	Lebanon	Lower middle income	15.6	Nascent	Nascent
87	COD	Congo, Dem. Rep.	Low income	14.6	Nascent	Nascent
88	HND	Honduras	Lower middle income	14.0	Nascent	Nascent
89	COM	Comoros	Lower middle income	12.2	Nascent	Nascent
90	COG	Congo, Rep.	Lower middle income	11.1	Nascent	Nascent
91	SLE	Sierra Leone	Low income	9.1	Nascent	Nascent
92	NIC	Nicaragua	Lower middle income	7.6	Nascent	Nascent
93	GIN	Guinea	Low income	7.4	Nascent	Nascent
94	LBR	Liberia	Low income	6.7	Nascent	Nascent
95	TCD	Chad	Low income	6.0	Nascent	Nascent
96	MDG	Madagascar	Low income	5.4	Nascent	Nascent
97	NER	Niger	Low income	0.0	Nascent	Nascent

Note: ABRI is the integral AI-Banking Readiness Index (0–100). Cluster: "Advanced" = advanced adopters, "Nascent" = nascent markets (k-means, k = 2). Quadrant from the median split of the demand and supply sub-indices: Integrated leaders (high–high), Demand-led (high demand, low supply), Supply-led (low demand, high supply), Nascent (low–low). Income groups follow the World Bank classification.

APPENDIX C. Correlation matrices

Panel A. ABRI input indicators (N = 97)

Pairwise Pearson correlations among the three demand indicators and the six GARI pillars that enter the composite. Variables are numbered in the first column; columns are identified by the same numbers.

Table C1. Pairwise Pearson correlations among the ABRI input indicators (N = 97)

Indicator	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. Digitally enabled account	1.00								
2. Made/received digital payment	0.55	1.00							
3. Saved formally	0.57	0.72	1.00						
4. Policy Capacity	0.35	0.49	0.46	1.00					
5. AI Infrastructure	0.42	0.74	0.67	0.68	1.00				
6. Governance	0.40	0.50	0.50	0.69	0.68	1.00			
7. Public Sector Adoption	0.41	0.59	0.46	0.64	0.69	0.69	1.00		
8. Development & Diffusion	0.34	0.53	0.57	0.82	0.79	0.75	0.60	1.00	
9. Resilience	0.35	0.45	0.45	0.70	0.64	0.65	0.53	0.65	1.00

Note: Lower triangle shown; diagonal = 1.00 (shaded). (1) digitally enabled account; (2) digital payment; (3) formal saving; (4) Policy Capacity; (5) AI Infrastructure; (6) Governance; (7) Public Sector Adoption; (8) Development and Diffusion; (9) Resilience.

Panel B. Cross-sectional regression variables (N = 93)

Pairwise Pearson correlations among the dependent variable and the regressors used in the cross-sectional models (Section 3.5), on the complete-case sample. This panel complements the variance-inflation factors reported with those models.

Table C2. Pairwise Pearson correlations among the cross-sectional regression variables (N = 93)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. Demand sub-index	1.00						
2. GARI overall	0.68	1.00					
3. Log GDP per capita	0.70	0.67	1.00				
4. Internet use	0.61	0.62	0.89	1.00			
5. Regulatory quality	0.54	0.59	0.60	0.50	1.00		
6. Domestic credit	0.44	0.45	0.41	0.48	0.35	1.00	
7. Tertiary enrollment	0.62	0.63	0.79	0.79	0.45	0.33	1.00

Note: Lower triangle shown; diagonal = 1.00 (shaded). (1) demand sub-index; (2) GARI overall; (3) log GDP per capita; (4) internet use; (5) regulatory quality; (6) domestic credit; (7) tertiary enrollment. All variables as defined in Appendix A.

APPENDIX D. Robustness of the ABRI ranking

The ABRI ranking is stable to the main construction choices. Each check below compares the country ranking under an alternative specification with the baseline ABRI ranking on the full sample (N = 97); the entry is the Spearman rank correlation with the baseline.

Table D1. Robustness of the ABRI ranking to alternative construction choices (Spearman ρ with the baseline ranking, N = 97)

Check	Specification	Spearman ρ
R1. Aggregation	Equal-weight average of the two sub-indices vs. the PCA-weighted integral index	1.000
R2. Indicator substitution	Three-indicator demand block replaced by account ownership (a single Findex indicator)	0.975
R3. Leave-one-pillar-out	Each GARI pillar dropped in turn; supply sub-index re-estimated on the remaining five	0.996–0.997

Note: Spearman rank correlations with the baseline ABRI ranking (N = 97). The integral index is built by two-stage PCA; "equal-weight" averages the two 0–100 sub-indices. R3 spans the six leave-one-out variants (minimum ρ = 0.996, dropping Public Sector Adoption). In R2, using the digital-account indicator instead of broad account ownership yields ρ = 0.931. The rankings are essentially preserved, confirming the index is not an artifact of the aggregation method or of any single component.

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