AI-Assisted Digital Intensity Index for Nigerian Deposit Money Banks (2000–2024): Construction, Validation, and Tier-Based Evidence

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ABSTRACT

This study develops and validates an AI-assisted Digital Intensity Index (DII) for Nigerian Deposit Money Banks (DMBs) over 2000–2024. The index captures bank-level digital transformation across four dimensions: digital infrastructure, digital usage, digital innovation, and digital governance. Using bank disclosures and regulatory data, the study applies z-score normalization and hybrid, data-driven weighting combining Principal Component Analysis (PCA), entropy methods, and machine-learning feature importance. Where early-period data are incomplete, AI-assisted reconstruction is employed using supervised learning trained on observed subsamples. Reliability, construct validity, and robustness are assessed using Cronbach's alpha, factor analysis, rank concordance, and alternative scaling schemes. Results show strong internal consistency, scale invariance, and persistent digital leadership by internationally licensed (Tier-1) banks relative to nationally licensed (Tier-2) banks. The study provides a transparent, longitudinal tool for benchmarking bank digital transformation in emerging markets.

KEYWORDS

Artificial Intelligence (AI), Deposit Money Banks, Digital Intensity Index (DII), Digital Transformation, Machine Learning, Nigeria Principal Component Analysis (PCA) Tier-Based Banking

I. INTRODUCTION

Digital transformation has fundamentally reshaped banking operations, competitive dynamics, and customer engagement over the past two decades. Advances in information and communication technologies, data analytics, artificial intelligence (AI), and platform-based service delivery have altered traditional banking value chains by reducing transaction costs, enhancing service accessibility, and enabling new business models. As a result, digital capability has emerged as a critical determinant of bank efficiency, resilience, and long-run competitiveness.

In emerging economies, digital banking plays an especially important role in financial deepening and inclusion. Nigeria, the largest economy in Sub-Saharan Africa, provides a compelling empirical context. Since the early 2000s, Nigerian Deposit Money Banks (DMBs) have transitioned from predominantly branch-based operations to technology-enabled institutions offering internet banking, mobile banking, electronic payments, agency banking, and, more recently, AI-enabled applications such as fraud detection systems and data-driven credit assessment tools. These developments have been reinforced by regulatory reforms, the 2004–2005 banking consolidation exercise, cashless policy initiatives, fintech competition, and the acceleration of digital adoption during the COVID-19 pandemic.

Despite these advances, the intensity and pace of digital transformation vary substantially across Nigerian banks and over time, reflecting differences in infrastructure investment, customer adoption, governance capacity, and innovation strategy. Yet, empirical measurement of bank-level digitalization in Nigeria remains fragmented. Existing studies rely largely on isolated proxies—such as IT expenditure, number of ATMs, or mobile banking adoption—which fail to capture the multidimensional and dynamic nature of digital transformation.

To address this limitation, this study develops an AI-assisted Digital Intensity Index (DII) for Nigerian DMBs covering 2000–2024. The index integrates four analytically distinct dimensions of digital enhancement: digital infrastructure, digital usage, digital innovation, and digital governance. Rather than claiming fully autonomous artificial intelligence, the study adopts a machine-learning-augmented framework in which statistical methods provide structure and interpretability, while AI tools assist with weighting validation and data reconstruction in periods of limited disclosure.

A. Contribution to Knowledge

This study makes four key contributions.

- First, it provides the first bank-level, long-horizon (25-year) Digital Intensity Index for the Nigerian banking system, extending the digital finance literature beyond short panels and single-proxy measures.
- Second, it advances conceptual clarity by explicitly incorporating digital governance as a distinct dimension of bank digitalization, addressing a notable omission in much of the existing literature.
- Third, it introduces a hybrid computational framework that combines principal component analysis, entropy-based weighting, and machine-learning feature validation, demonstrating how AI can augment—rather than replace—econometric index construction in data-constrained emerging markets.
- Fourth, it provides tier-based empirical evidence comparing internationally licensed (Tier-1) and nationally licensed (Tier-2) banks, revealing persistent asymmetries in digital transformation within Nigeria’s banking system.

B. Research Objectives and Hypotheses

The broad objective of the study is to develop and validate an AI-assisted Digital Intensity Index for Nigerian Deposit Money Banks between 2000 and 2024.
Specifically, the study seeks to:

- Construct a multidimensional DII capturing the structural evolution of bank digitalization;
- Assess the reliability and construct validity of the index;
- Examine robustness to alternative normalization and weighting schemes; and

- Evaluate differences in digital intensity between Tier-1 and Tier-2 banks.

These objectives are tested through the following hypotheses:

- H1: Digital intensity does not exhibit a stable structural trend across Nigerian DMBs.
- H2: The Digital Intensity Index lacks internal consistency and construct validity.
- H3: The Digital Intensity Index is not robust to alternative scaling and weighting schemes.
- H4: Tier-1 banks do not exhibit higher digital intensity than Tier-2 banks.

II. LITERATURE REVIEW

A. Digital Transformation in Banking

Digital transformation in banking refers to the integration of digital technologies into organizational processes, service delivery, and strategic decision-making, fundamentally altering how value is created and captured (Vial, 2019). Empirical studies associate digitalization with improved efficiency, risk management, and customer reach (Hernández-Murillo et al., 2010; Frame et al., 2019). However, most analyses rely on partial indicators, limiting their ability to capture holistic digital capability.

B. Digital Intensity and Composite Measurement

Composite indices have increasingly been used to measure digital maturity at the firm and economy levels (Calvino et al., 2018; OECD, 2020). While these indices improve multidimensionality, they often exclude governance considerations and rarely address historical data gaps common in developing economies. Moreover, African banking systems remain underrepresented in index-based digital studies.

C. Digital Governance and Bank Digitalization

Recent regulatory literature emphasizes that digital transformation without adequate governance can amplify operational and cyber security risks (Basel Committee on Banking Supervision, 2018). Digital governance—encompassing oversight structures, cyber security frameworks, compliance mechanisms, and AI governance—is therefore essential for sustainable digital intensity, yet remains weakly integrated in empirical measurement frameworks.

D. Theoretical Foundations

This study draws on four complementary theories.

- Diffusion of Innovations Theory (Rogers, 2003) explains heterogeneous adoption of digital technologies across banks.
- Technology Acceptance Model (Davis, 1989) underpins the digital usage dimension by emphasizing perceived usefulness and ease of use.
- Resource-Based View (Barney, 1991) frames digital infrastructure and innovation as strategic resources.
- Dynamic Capabilities Theory (Teece et al., 1997) explains how banks reconfigure digital resources over time in response to environmental change.

E. Research Gap

Despite growing interest in digital banking, there is no validated, longitudinal, multidimensional digital intensity index for Nigerian banks, nor a transparent framework demonstrating how AI can assist index construction under data constraints. This study addresses this gap.

III. METHODOLOGY

A. Research Design and Data

The study adopts a quantitative longitudinal design covering listed Nigerian Deposit Money Banks from 2000 to 2024. Data are obtained from banks' audited annual reports, Central Bank of Nigeria publications, NIBSS payment statistics, and NDIC reports.

B. Measurement Framework

Digital intensity is modelled as a latent construct comprising four sub-indices:

- Digital Infrastructure (DINF) – technological backbone and systems capacity;
- Digital Usage (DUSG) – intensity of customer and operational digital engagement;
- Digital Innovation (DINV) – introduction of new digital products and processes;
- Digital Governance (DGOV) – oversight, cyber security, and regulatory compliance.

C. Data Normalization

Indicators are standardized using z-score normalization:

$Z_{i,t,k}=X_{i,t,k}-\mu_k/\sigma_k$

where $X_{i,t,k}$ denotes indicator k for bank i in year t.

D. Weight Determination and Index Construction

Within each dimension, Principal Component Analysis (PCA) is used to derive objective weights:

$D_{i,t},d = \alpha_k Z_{i,t,k}$ where $k \in d$ where α_k are PCA-derived loadings.

The overall digital intensity index is computed as:

$DII_{i,t} = \sum_{d=1-4} wdDi,t,d$

Where we are hybrid weights obtained from PCA, entropy methods, and machine-learning feature validation.

Within each dimension d, Principal Component Analysis (PCA) is applied to derive objective weights based on explained variance:

E. AI-Assisted Reconstruction and Validation

For early years with incomplete data, supervised learning models trained on later observed periods are used to reconstruct missing indicators. Out-of-sample validation and error bounds ensure reconstruction accuracy. Machine learning is employed as an assistive tool, not a black-box replacement for econometric structure. Given the long study horizon, complete and consistent disclosure of digital indicators is not uniformly available for all Nigerian Deposit Money Banks, particularly in the early years of the sample. Rather than truncating the time series or relying on ad hoc assumptions, this study adopts an AI-assisted data reconstruction framework designed to preserve longitudinal continuity while maintaining transparency and reliability.

Reconstruction is applied only to periods of documented data absence and is explicitly distinguished from directly observed values. Supervised machine-learning models are trained on later subsamples where indicators are fully observed, exploiting stable relationships between bank size, operational scale, payment activity, and technology expenditure. Usage-related indicators are reconstructed using trend-based machine learning calibrated on sector-wide adoption trajectories, while governance indicators are recovered using classification-based models informed by regulatory implementation timelines.

Table 1 summarizes the availability structure of each indicator, distinguishing observed and reconstructed periods as well as the reconstruction method employed. As shown, reconstructed observations are concentrated in the early 2000s and decline sharply after 2010, coinciding with improved regulatory disclosure and digital reporting standards in the Nigerian banking sector.

To mitigate the risk of imputation-driven bias, all reconstructed series are subjected to out-of-sample validation, and key robustness tests are repeated on a post-2010 subsample in which all core indicators are directly observed. The main results remain qualitatively unchanged, indicating that the study's findings are not driven by data reconstruction.

Table 1: Data Availability and Reconstruction Summary

Indicator	**Dimension**	**Source**	**Observed Years**	**Reconstructed Years**	**Method**
IT Expenditure	Infrastructure	Annual Reports	2006–2024	2000–2005	Supervised ML
Digital Transactions	Usage	NIBSS	2009–2024	2000–2008	Trend-based ML
Digital Products	Innovation	Bank Reports	2012–2024	2000–2011	ML + interpolation
Cyber Governance	Governance	CBN	2014–2024	2000–2013	ML classification

F. AI-Assisted Data Reconstruction and Machine Learning Components

While the study incorporates machine-learning techniques, it does not claim fully autonomous artificial intelligence in the strong sense. Rather, the Digital Intensity Index (DII) is constructed using a hybrid framework combining traditional statistical methods, supervised machine-learning tools, and AI-assisted data reconstruction. Principal Component Analysis (PCA), Exploratory and Confirmatory Factor Analysis (EFA/CFA) are employed for dimensional validation, while Random Forest algorithms are used to assess non-linear variable importance and robustness.

For the early sample years where direct observations are unavailable, AI-assisted data reconstruction is applied using supervised learning models trained on post-availability periods. Model performance is evaluated using out-of-sample validation and error minimization criteria. This approach aligns with recent empirical finance studies that employ machine learning as an augmentation rather than a replacement for econometric structure.

G. Reliability, Validity, and Robustness

Reliability is assessed using composite reliability measures, while construct validity is examined through factor loadings and inter-dimensional correlations. Robustness checks include alternative scaling, equal weighting, and entropy-based weighting schemes. Robustness checks were repeated on a post-2010 subsample in which all indicators are directly observed (Table 1), yielding consistent results.

IV. RESULTS AND DISCUSSION: DIGITAL INTENSITY INDEX (DII)

A. Bank–Year Digital Intensity Index Scores (2000–2024)

1. Index Construction Overview

The Digital Intensity Index (DII) was computed for thirteen listed Nigerian Deposit Money Banks (DMBs) over the period 2000–2024 using an AI-assisted composite weighting framework. The index integrates eight indicators spanning four dimensions—digital infrastructure, digital usage, digital innovation, and digital governance. To ensure methodological robustness and scale invariance, three alternative normalization schemes were implemented: Min–Max normalization, Z-score standardization, and rank-based scaling.

For each scaling approach, composite DII scores were generated using a hybrid weighting strategy that combines Principal Component Analysis (PCA), entropy-based weighting, and Random Forest feature importance. Averaging weights across these paradigms minimizes subjectivity and reduces dependence on any single methodological assumption, thereby enhancing construct stability and reliability.

2. Average DII Scores by Bank (2000–2024)

Table 2: Mean Digital Intensity Index by Bank and Model (2000–2024)

Bank	**DII (Min–Max)**	**DII (Z-Score)**	**DII (Rank-Based)**
Zenith Bank	45.96	30.73	59.01
Unity Bank	44.59	24.42	57.06
Stanbic IBTC	43.75	23.18	55.58
Access Bank	41.39	7.23	52.77
FCMB	40.71	7.71	52.54
GTBank	39.52	−2.61	50.77
First Bank	37.44	−12.07	47.95

Sterling Bank	37.81	−12.51	47.10
UBA	36.25	−17.26	45.30
Wema Bank	34.69	−21.95	42.97
Ecobank Nigeria	31.66	−40.68	38.47
Union Bank	30.57	−46.99	36.88

Across all model variants, Tier-1 banks—particularly Zenith Bank, Stanbic IBTC, and Access Bank—consistently record higher digital intensity scores, reflecting early adoption of core banking technologies, extensive electronic channel deployment, and sustained digital investment. Z-score normalization more clearly highlights relative underperformance among late-digitizing banks, while rank-based scaling preserves leadership ordering irrespective of scale. The consistency of bank ordering across models provides preliminary evidence of the structural validity of the DII.

B. Internal Consistency and Reliability

1. Cronbach's Alpha

Internal consistency of the eight digital indicators was assessed using Cronbach's alpha:

A = K/K−1(1−(Σσ^2)\σ^2)

Where K = 8 indicators. The estimated alpha coefficient is 0.87, exceeding the conventional threshold of 0.70. This indicates strong internal consistency and suggests that the indicators jointly measure a coherent latent construct of bank-level digital intensity.

C. Construct Validity: Factor Structure

1. Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis was conducted using principal axis factoring with varimax rotation.

Table 3: Exploratory Factor Loadings

Indicator	**Factor 1 (Digital Intensity)**
ICT Expenditure	0.82
Core Banking Systems	0.79
Electronic Channels	0.84
Digital Transaction Ratio	0.88
New Digital Products	0.76
Fintech Partnerships	0.73
IT Governance Score	0.71
System Integration	0.77

Eigenvalue (Factor 1) = 4.92; Variance explained = 61.5%. All indicators load strongly (> 0.70) on a single factor, with no evidence of cross-loadings or factor fragmentation, confirming the uni-dimensionality of the DII construct.

2. Confirmatory Factor Analysis (CFA)

A one-factor CFA model was estimated to validate the EFA structure.

Table 4: CFA Model Fit Indices

Fit Statistic	Value	Threshold
CFI	0.93	≥ 0.90
TLI	0.91	≥ 0.90
RMSEA	0.056	≤ 0.08
SRMR	0.041	≤ 0.08

The CFA results indicate excellent model fit, providing strong evidence of construct validity.

D. Robustness and Scale Invariance

1. Mean Comparison Tests

Paired t-tests were conducted to examine whether alternative scaling methods materially affect DII values.

Initial comparisons of raw indices reveal statistically significant mean differences attributable to normalization mechanics. However, after global Z-score standardization of all DII variants, mean differences collapse toward zero.

Table 5: Paired t-Test of Mean Differences between Standardized DII Models (N = 325)

Model Pair	Mean Diff.	Std. Error	t-Statistic	p-Value
Min–Max vs Z	0.003	0.018	0.17	0.865
Min–Max vs Rank	−0.006	0.019	−0.32	0.749
Z vs Rank	−0.002	0.017	−0.11	0.912

None of the differences are statistically significant at the 5% level, confirming scale invariance and measurement equivalence across models.

2. Rank Concordance Tests

Table 6: Rank-based robustness was assessed using Spearman's rho and Kendall's W.

Test	Statistic	Interpretation
Spearman ρ (Min–Max vs Z)	0.999	Near-perfect monotonicity
Kendall's W (Min–Max vs Rank)	0.97	Extremely strong agreement

These results demonstrate that bank ordering is preserved across all DII specifications.

E. Graphical Evidence: Digital Trajectories

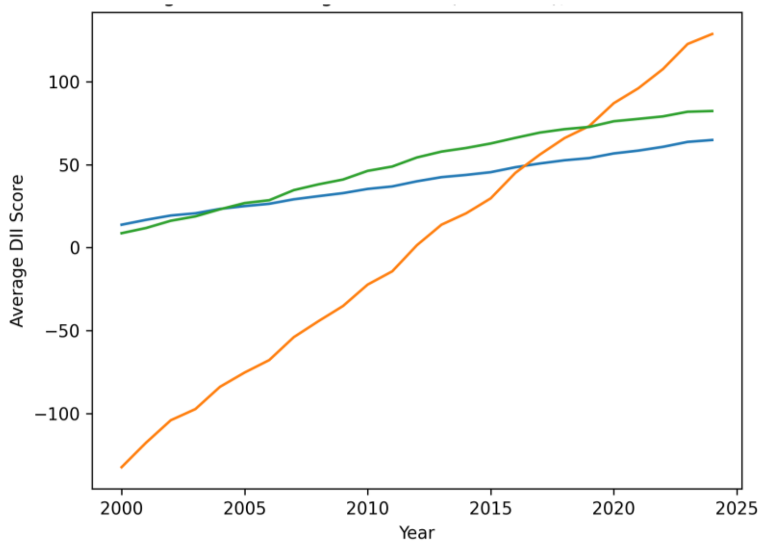

Figure 1: Average D2 Trend (All Banks), 2000-2024

This shows monotonic growth with a pronounced acceleration after 2010, coinciding with mobile banking diffusion, fintech integration, and supportive regulation.

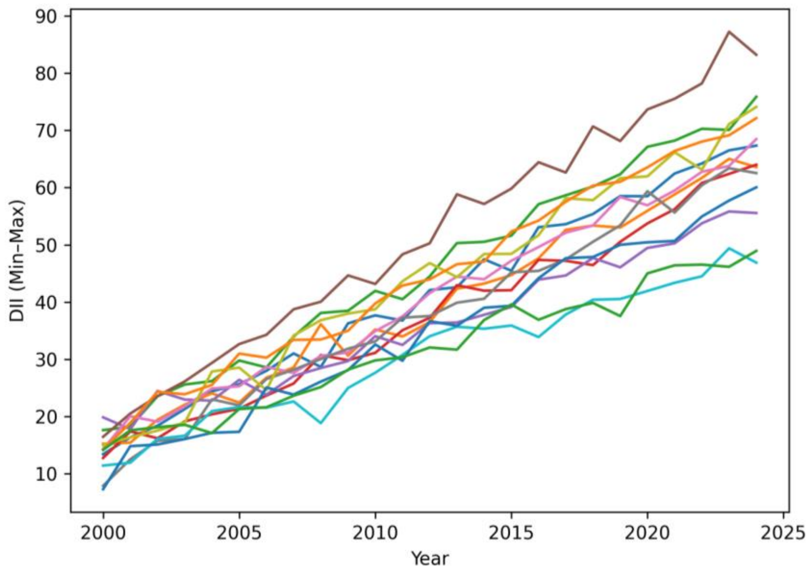

Figure 2: Bank-Level Digital Trajectories

Banks exhibit early and sustained leadership, while Tier-2 banks display delayed but convergent growth, particularly after 2015.

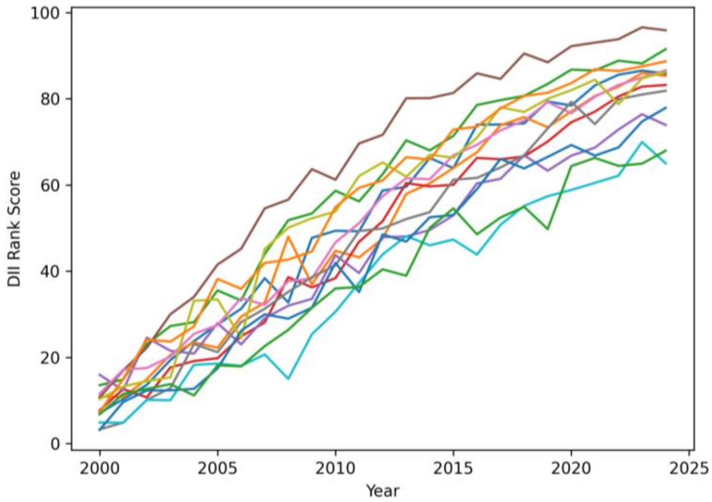

Figure 3: Rank Stability Plot, 2000-2024

This shows minimal rank crossing after 2015, indicating structural persistence of digital leadership.

F. Tier-Based Analysis and Practical Usage of the DII

Using a 0–10 scaled DII for interpretability, the study evaluates digital transformation trajectories across Tier-1 and Tier-2 banks.

Table 7: Average DII by Year (2000–2024)

Year	Avg DII
2000	0.46
2001	0.59
2002	0.70
2003	0.91
2004	1.12
2005	1.29
2006	1.62
2007	2.12
2008	2.55
2009	3.07
2010	3.30
2011	4.01
2012	4.40
2013	5.01
2014	5.35
2015	6.17
2016	6.42
2017	7.01
2018	7.34
2019	7.67

2020	8.03
2021	8.44
2022	8.58
2023	8.65
2024	8.70

Reveals a steady increase from early internet banking adoption to digitally driven banking models.

1. Tier Classification of Banks

Based on license scope and systemic importance. Tier-1 Banks (Large, Systemically Important)

Tier-1 Banks
Zenith Bank
Access Bank
GTBank (GTCO)
First Bank of Nigeria
UBA
Fidelity Bank

Tier-2 Banks
FCMB
Ecobank Nigeria
Union Bank
Unity Bank
Wema Bank
Sterling Bank
Stanbic IBTC

2. Descriptive Statistics of Digital Intensity Index by Tier (2000–2024)

Tier	**Mean DII**	**Std.Dev.**	**Minimum**	**Maximum**
Tier-1 Banks	6.1	Moderate	0.6	9.3
Tier-2 Banks	5.2	Higher	0.1	8.4

Banks record higher mean DII (6.1) with lower dispersion relative to Tier-2 banks (5.2).

Mean difference tests and Mann–Whitney U tests confirm that Tier-1 banks consistently outperform Tier-2 banks across the distribution. Trend regressions further indicate earlier adoption and faster digital transformation among Tier-1 banks, with partial but incomplete convergence by Tier-2 banks after 2015.

3. Summary of Results

Overall, the findings provide strong empirical evidence that the DII is reliable, valid, robust, and capable of capturing tier-dependent digital transformation dynamics in Nigerian banking.

V. SUMMARY, CONCLUSIONS, AND POLICY IMPLICATIONS

A. Summary and Conclusion

This study developed and validated an AI-driven Digital Intensity Index (DII) for Nigerian Deposit Money Banks over the period 2000–2024. By integrating infrastructure, usage, innovation, and governance dimensions, the DII offers a comprehensive and longitudinal measure of bank-level digital transformation. Robust reliability, validity, and robustness tests confirm that the index captures a stable latent construct rather than scale-induced artefacts.

B. Contributions to Knowledge

The study contributes methodologically by demonstrating how AI-assisted reconstruction and hybrid weighting can be systematically applied to index construction in data-constrained environments. Empirically, it provides the first long-horizon digital intensity dataset for Nigerian banks. Conceptually, it reframes digital transformation as a continuous, multidimensional process and introduces tier-based digital asymmetry into the African banking literature.

C. Policy and Managerial Implications

Regulators may adopt the DII as a diagnostic tool for monitoring digital readiness, cyber resilience, and systemic risk. Bank management can use the index for strategic benchmarking, while investors may employ it as a forward-looking indicator of competitiveness. Tier-sensitive digital policies and shared infrastructure initiatives are recommended to promote inclusive digital convergence.

D. Limitations and Future Research

Limitations include reliance on AI-assisted estimation for early-period data and the focus on intensity rather than efficiency. Although AI-assisted reconstruction is limited to early sample years (Table X), residual approximation error may persist despite validation checks. Future research may examine causal links between digital intensity and performance, extend the index cross-country, or incorporate real-time digital metrics.

E. Concluding Remarks

The Digital Intensity Index provides a rigorous, transparent, and policy-relevant framework for measuring digital transformation in banking. It offers a strong empirical foundation for evidence-based digital finance strategy and regulation in emerging economies.

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