



Article

Channel Observability in Digital Financial Inclusion Measurement: A Diagnostic Study of OIC Countries, 2015–2024

Nassar Al-Hafidh ¹, Ahmed Lateef Salih Al-Karawi ^{2,3}, Hayder Albayati ^{4,*} and Erginbay Uğurlu ⁵

¹ Faculty of Business Management, Istanbul Aydın University, Istanbul 34035, Türkiye; nbasharal-hafidh@stu.aydin.edu.tr

² Defne Telekomünikasyon A.Ş., Maslak Mahallesi, Maslak Meydan Sokak, Spring Giz Plaza, No: 5, İç Kapı: 37, Kat: 9, Sarıyer, Istanbul 34485, Türkiye; ahmedal-karawi@stu.aydin.edu.tr

³ Department of Computer Engineering, Faculty of Engineering, Istanbul Aydın University, Istanbul 34295, Türkiye

⁴ Endicott College, Woosong University, Daejeon 34606, Republic of Korea

⁵ Department of Economics and Finance, Istanbul Aydın University, Istanbul 34295, Türkiye; erginbayugurlu@aydin.edu.tr

* Correspondence: hayder1111@wsu.ac.kr

Abstract

Digital financial inclusion (DFI) has become a central topic in financial inclusion research because digital payments, mobile money, internet banking, and platform-based finance can reduce access barriers and expand formal financial participation. Prior studies have documented the development relevance of financial inclusion and have constructed multi-dimensional financial inclusion and DFI indices, often using PCA and related composite-indicator methods. A remaining measurement gap concerns the equal observability of different digital-finance architectures within a common cross-country indicator set. This study addresses that gap by analyzing an existing PCA-based DFI score for 40 Organisation of Islamic Cooperation (OIC) countries over 2015–2024 through a channel-observability framework. The objective is to examine whether the observed DFI ranking is captured more directly through mobile-money indicators than through the available infrastructure-based representation of bank-led digital finance. The analysis decomposes the six available indicators into a bank-led visibility proxy, based on internet penetration and ATM density, and a mobile-money visibility proxy, based on mobile agents, mobile accounts, mobile transaction volume, and transaction value relative to GDP. The OIC-wide mean DFI score increased from 11.31 in 2015 to 31.24 in 2024, while dispersion widened and the 2015 and 2024 top-ten country groups had zero overlap. The channel diagnostics show that the highest observed DFI scores are concentrated among countries whose digital-finance activity is directly recorded through mobile-money indicators, whereas several financially advanced economies are visible mainly through the bank-led infrastructure proxy. Zero-coded mobile-money observations are interpreted as indicator-visibility signals for the standalone mobile-money channel and considered separately from broader digital-finance activity. The Random Forest analysis functions as a bounded internal sensitivity audit of the existing six-indicator score and shows that mobile-money transaction variables carry the largest within-score explanatory weight. The theoretical contribution is to frame DFI measurement as an architecture-dependent observability problem rather than only as a weighting problem. The practical implication is that cross-country DFI rankings should be interpreted together with channel diagnostics, especially when bank-led digital services such as mobile banking, card payments, POS transactions, QR payments, and instant-payment systems are outside the balanced indicator set.



Academic Editor: You Zhu

Received: 29 May 2026

Revised: 11 July 2026

Accepted: 13 July 2026

Published: 20 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons](https://creativecommons.org/licenses/by/4.0/)

[Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: digital financial inclusion; channel observability; mobile money; bank-led digital finance; OIC countries; financial inclusion measurement; PCA index; digital payments; external validation

JEL Classification: G20; G21; O16; O33; O57

1. Introduction

Digital financial inclusion (DFI) has become a central policy objective because digital payments, mobile financial services, and online banking can reduce transaction costs, extend formal finance to underserved users, and improve the ability of households and firms to manage economic shocks. The World Bank Global Findex program treats financial inclusion as a broad multidimensional concept covering account ownership, payments, saving, borrowing, and risk management, and recent Findex work also emphasizes mobile phone ownership, internet use, and digital safety as enabling conditions for financial participation (Demirguc-Kunt et al., 2022; World Bank, 2025). The International Monetary Fund (IMF) similarly treats DFI as a broad process involving mobile-money operators, fintech firms, new digital financial providers, and internet or mobile banking services delivered by traditional banks (Khera et al., 2021a, 2021b). This conceptual breadth is important because DFI is not a single technology or one uniform institutional model; it is a set of digital channels through which formal financial services become accessible, usable, and scalable.

The significance of this topic is that DFI indicators increasingly inform cross-country benchmarking, policy prioritization, and development-finance narratives, yet the same numerical score may not have the same meaning across countries with different financial architectures. Prior studies have established the role of financial inclusion and digital payments in development, growth, resilience, and poverty reduction, and they have also proposed multidimensional DFI indices using access and usage indicators. The remaining gap is narrower but important: less attention has been given to whether internationally comparable DFI indicators observe mobile-money-led and bank-led digital-finance systems with the same intensity. This gap matters for OIC countries because the sample combines mobile-money-intensive African economies, bank-led Gulf economies, and hybrid middle-income systems in the same ranking exercise.

The same breadth creates a measurement problem. In economies where digital finance is organized through mobile-money ecosystems, inclusion is directly visible through internationally reported indicators such as mobile-money agents, mobile accounts, mobile transaction volumes, and mobile transaction values. In financially advanced economies, however, digital financial activity may be embedded inside bank accounts, banking applications, debit and credit card networks, POS terminals, QR payments, instant-payment rails, and digital government-payment systems. These bank-led channels may perform many of the same economic functions as mobile wallets, while appearing in international data through different reporting categories rather than through separate mobile-money indicators. The IMF Financial Access Survey (FAS) distinguishes mobile money from mobile and internet banking: mobile money is typically independent of a traditional bank account and supported by mobile-money agents, whereas mobile or internet banking refers to the execution of banking services through electronic devices or applications (IMF, 2017, 2025). This distinction is central for interpreting cross-country DFI rankings.

The Organisation of Islamic Cooperation (OIC) provides a particularly useful empirical setting for examining this problem. OIC economies include high-income Gulf and Asian

countries, middle-income banking economies, and less-developed but mobile-money-intensive African economies. A single DFI ranking can therefore combine countries whose digital finance is bank-led with countries whose digital finance is mobile-money-led (Jack & Suri, 2011). If the available indicator system observes one architecture more directly than another, the resulting ranking may reflect channel visibility as well as genuine inclusion outcomes. The issue is therefore best understood as a measurement-interpretation problem inherited from the structure and availability of internationally comparable DFI indicators.

This paper develops a channel-observability perspective for interpreting DFI measurement. Channel observability refers to the extent to which a given digital-finance architecture is directly represented in the available indicator set. The research objective is to examine whether the existing 2015–2024 DFI ranking for 40 OIC countries is partly shaped by the observability of different digital-finance channels. The analysis therefore moves beyond the question of which country ranks highest and evaluates how the observed ranking reflects the indicator channels through which digital finance becomes visible in internationally comparable data. Accordingly, this study uses the language of channel observability and possible under-observation as the analytical vocabulary for a diagnostic interpretation of the existing score.

The aim and novelty of this paper are the provision of a transparent channel-observability diagnostic for an existing OIC DFI score. The study separates the available indicators into bank-led and mobile-money visibility families, examines rank mobility, identifies possible under-observation candidates, and uses a Random Forest model as an internal sensitivity audit of the constructed score. The contribution is interpretive and methodological: it strengthens the reading of existing DFI rankings by linking score interpretation to the institutional architecture through which digital finance is observed.

The remainder of this paper is organized as follows: Section 2 reviews the literature on DFI measurement, mobile money, bank-led digital finance, and composite indicators. Section 3 explains the methodology, data sources, variable construction, and diagnostic rules used to assess channel visibility. Section 4 presents the empirical results. Section 5 discusses the implications for measurement validity and OIC policy interpretation. Section 6 concludes.

2. Literature Review

To maintain terminological consistency, this paper uses digital finance as the broader supply-side and infrastructure concept covering digital-payment systems, bank applications, mobile-money platforms, cards, POS networks, QR payments, and instant-transfer rails. It uses digital financial inclusion to refer to the access, adoption, usage, and inclusion outcomes generated when households and firms can use those digital financial channels. The term bank-led digital finance refers to digital services embedded in regulated banking and payment infrastructures, whereas mobile-money-led digital finance refers to services separately organized and reported through mobile-money providers, accounts, agents, and transactions.

2.1. Theoretical Motivation and Research Gap

The theoretical starting point of the paper is that financial inclusion is not only an access outcome but also an institutional-delivery process. Earlier work links broader financial access to development, poverty reduction, and inclusive growth (Beck et al., 2007; Demirgüç-Kunt & Klapper, 2013; Sarma & Pais, 2011). The digital-finance literature extends this view by showing that technology can change the cost, reach, speed, and institutional form of financial-service delivery (Demir et al., 2022; Gomber et al., 2017; Ozili, 2018). Mobile-money studies further show that agent-based and phone-based payment ecosystems can generate

measurable welfare and inclusion effects where conventional banking infrastructure is sparse (Suri, 2017; Suri & Jack, 2016).

These studies provide the background for the present paper and leave a measurement problem that emerges when different digital-finance architectures are ranked with the same indicator set. Most composite DFI measures ask how to combine available indicators into a single score. This paper asks a narrower question: whether the available indicators observe mobile-money-led and bank-led digital-finance systems with equal directness. The research gap is therefore not the absence of DFI indices, but the limited treatment of indicator visibility as a source of interpretation risk in cross-country DFI rankings. The theoretical originality of this paper lies in framing DFI measurement as an architecture-dependent observability problem: the same user-facing outcome may be produced through mobile-money accounts, bank accounts, payment cards, QR systems, or instant-payment rails, but only some of these channels may leave direct traces in internationally comparable data.

2.2. Digital Financial Inclusion as a Multi-Channel Concept

Financial inclusion refers to meaningful access to and active use of formal financial services by households and firms. Earlier studies emphasized physical access to bank branches, deposit accounts, credit, and payment services (Demirguc-Kunt & Klapper, 2013; Sarma, 2008; Sarma & Pais, 2011). Digital transformation expanded this framework by introducing mobile money, internet banking, digital payments, fintech platforms, and data-driven credit channels (Klapper et al., 2016). Digital financial services can reduce fixed transaction costs and allow providers to reach users who were previously excluded by distance, documentation requirements, or small transaction size (Demir et al., 2022; Gomber et al., 2017; Ozili, 2018). This distinction strengthens the conceptual framework of the paper: digital finance is the delivery architecture, whereas DFI is the inclusion outcome generated when users can access and use that architecture.

However, DFI is technologically heterogeneous. Mobile money has been especially transformative in several African economies because it can operate outside dense branch networks and can be supported by agent networks, basic mobile phones, and low-cost transaction platforms (Aker & Mbiti, 2010; Jack & Suri, 2014). In contrast, many high-income or financially advanced economies rely less on standalone mobile-money agent systems because digital finance is already embedded inside formal banking systems. In these settings, relevant digital-finance channels include bank applications, internet banking, debit and credit cards, POS networks, instant-payment systems, contactless payments, QR payments, and public digital-payment infrastructures. A valid DFI interpretation must therefore distinguish between digital inclusion that is visible through mobile-money indicators and digital inclusion that is embedded inside bank-led systems.

2.3. Composite DFI Indices and the Indicator-Visibility Problem

Composite indices are widely used to summarize multidimensional concepts such as financial inclusion, financial development, and digital access (Camara & Tuesta, 2014; Nardo et al., 2008; Svirydzienka, 2016). PCA-based weighting is frequently used because it derives weights from the covariance structure of standardized indicators rather than relying on equal or subjective weights (Filmer & Pritchett, 2001; Kaiser, 1960). The advantage of a PCA-based DFI score is therefore parsimony: it reduces several correlated access and usage indicators to a single comparable measure while limiting purely subjective weighting choices. This feature is valuable for cross-country benchmarking, especially when the objective is to summarize multidimensional variation in a transparent statistical form. Prior DFI studies have used access and usage indicators to build cross-country measures and to examine the relationship between DFI, growth, inequality, poverty reduction, and financial development (Khera et al., 2021a, 2021b; Kouladoun et al., 2022).

The construction of an internally coherent composite index requires interpretation alongside the channels available as comparable indicators. Mobile-money ecosystems generate direct and standardized variables such as agent density, registered accounts, transaction volume, and transaction value. Bank-led ecosystems may generate equally important digital financial activity through bank-account usage, payment-card networks, instant transfers, or payment applications that leave different traces in international datasets. Thus, a statistically valid DFI index can be strengthened by an explicit channel-observability interpretation that identifies which forms of digital finance are directly represented in the indicator set.

2.4. Channel Observability and Measurement Interpretation

This study treats channel observability as a measurement-interpretation condition in which one digital-finance architecture is more directly visible in the available indicator set than another. In the present dataset, mobile-money-led systems are directly visible because four of the six indicators measure mobile-money infrastructure or usage, whereas bank-led digital finance is represented through internet penetration and ATM density. Mobile-money variables are essential for measuring digital inclusion in countries where mobile wallets and agents are the dominant inclusion channel. The diagnostic becomes important when the same indicator structure is used to compare countries where digital finance is delivered mainly through bank accounts, banking applications, card systems, POS networks, QR payments, or instant-transfer infrastructures. This study therefore interprets the DFI ranking as a channel-dependent measurement outcome and reserves stronger claims about bias for future work with direct external validation data.

The conceptual distinction is supported by IMF definitions. Mobile money can operate independently of a bank account and is facilitated through mobile-money service providers and agent networks, whereas mobile and internet banking refers to digital execution of banking services through mobile or electronic devices (IMF, 2017, 2025). Therefore, comparing countries with different dominant channels requires more than reporting a single score. It requires a diagnostic interpretation of the channel structure behind that score.

3. Methodology

3.1. Data Sources, Variable Construction, and Analytical Objective

This study uses a balanced panel of 40 OIC countries observed annually from 2015 to 2024, producing 400 country-year observations. The raw variables were compiled from internationally comparable financial access and development data sources, principally IMF Financial Access Survey-style indicators for financial access and mobile money and World Bank data sources for internet-related digital access. The analytical file is a cleaned research panel constructed from harmonized source institutions and consistently defined variables. The empirical object is the PCA-based DFI score, denoted DFI_{it} , normalized to a 0–100 scale and constructed from the six indicators listed in Table 1. The analysis preserves this six-indicator score and examines its channel structure by assessing whether the observed ranking is more directly visible through mobile-money indicators than through the available bank-led infrastructure proxy. This design keeps the empirical object stable while adding an explicit measurement-interpretation layer to the existing DFI ranking.

Each variable has a specific interpretation in this diagnostic design. Internet penetration captures broad digital connectivity and is relevant because online banking, banking applications, QR payments, and instant-payment interfaces require digital access. ATM density captures conventional banking-infrastructure visibility and serves as a supply-side representation of bank-led financial infrastructure. Mobile agents per 100,000 adults capture the physical distribution network of mobile-money services. Mobile accounts per

1000 adults capture mobile-money adoption. Mobile transactions per 1000 adults capture usage intensity, and mobile transaction value relative to GDP captures transaction depth. These interpretations clarify the distinction between directly reported mobile-money usage variables and infrastructure-based variables that represent the observable bank-led channel within the balanced panel.

Table 1. Indicator grouping for channel-observation diagnosis.

Channel Family	Indicators	Interpretation
Bank-led digital visibility	Internet penetration; ATMs per 100,000 adults	General digital access and conventional banking infrastructure visible in the index
Mobile-money visibility	Mobile agents per 100,000 adults; mobile accounts per 1000 adults; mobile transactions per 1000 adults; mobile transaction value/GDP	Separately reported mobile-money access, adoption, transaction volume, and transaction depth

Note: ATM = Automated Teller Machine; GDP = Gross Domestic Product. The table separates the six DFI indicators into two observable channel families: bank-led digital visibility and mobile-money visibility. This grouping functions as a diagnostic decomposition used to interpret which digital-finance architecture is more visible in the observed DFI score. The bank-led proxy represents the bank-led channel through infrastructure and digital-access variables available in the balanced panel. Direct indicators such as mobile banking transactions, online banking use, card payments, POS transactions, QR payments, and instant-payment-system usage have uneven cross-country and annual coverage across the full 2015–2024 period.

The DFI score is calculated in two transparent steps. First, the six raw indicators are transformed into standardized variables, denoted Z_{ijt} , where $j = 1, \dots, 6$ indexes the indicators, i indexes countries, and t indexes years. Second, the standardized indicators are combined using the PCA-derived weights associated with the composite score. The unscaled PCA composite is expressed as:

$$DFI_{it}^* = \sum_{j=1}^6 w_j Z_{ijt}, \quad (1)$$

where w_j denotes the PCA-derived weight assigned to indicator j . The final DFI score is then normalized to a 0–100 scale as follows:

$$DFI_{it} = 100 \times \frac{DFI_{it}^* - \min(DFI^*)}{\max(DFI^*) - \min(DFI^*)}. \quad (2)$$

In Equation (2), $\min(DFI^*)$ and $\max(DFI^*)$ refer to the lower and upper bounds of the unscaled PCA composite in the normalization sample. This notation makes the DFI construction explicit for readers who are less familiar with PCA-based composite indicators and preserves the score, weights, and country rankings used in the channel-observability analysis. The PCA approach is appropriate because it converts correlated indicators into a compact score and reduces reliance on arbitrary equal-weight aggregation. Because PCA weights the indicators available in the dataset, the interpretation of the resulting DFI score depends on the breadth of the observed indicator set. This property makes PCA suitable for summarization while also motivating the present channel-level interpretation.

The six indicators are grouped into two observable channel families. Internet penetration represents general digital connectivity and is necessary for many forms of online and mobile banking. ATM density represents conventional banking access and financial infrastructure. Together, these two variables provide an infrastructure-based bank-led visibility proxy within the balanced annual panel. Direct transaction-level indicators for online banking, mobile banking, card payments, POS transactions, QR payments, and instant-payment-system activity lie outside the harmonized 2015–2024 dataset. The mobile-money

visibility proxy uses mobile agents, mobile accounts, mobile transactions, and mobile transaction value relative to GDP because these indicators directly represent separately reported mobile-money access and usage. Table 1 defines this grouping and clarifies that the decomposition is used to interpret channel visibility within the available data.

Missing Data, Non-Reporting, and Zero-Visibility Coding

A further data-processing issue concerns mobile-money observations that are reported as zero or are not separately reported for economies where standalone mobile-money infrastructure is not the dominant delivery channel. The coding strategy separates numerical indicator visibility from substantive digital-finance activity. A zero-coded mobile-money observation represents zero visibility for the standalone mobile-money indicator in the analytical file rather than the absence of all digital-finance services in the country. This distinction is important because bank-led digital services can operate through banking applications, card networks, POS systems, QR payments, instant-payment rails, and government-payment platforms even when standalone mobile-money variables are not reported.

For several financially advanced economies in the sample, standalone mobile-money indicators are frequently absent from global databases because digital finance is organized mainly through bank-led and embedded payment channels rather than through mobile-money agent networks. The affected cases include Saudi Arabia, the United Arab Emirates, and Malaysia, which have zero observations across all four mobile-money indicators in the analytical file, together with Bahrain, Morocco, and Türkiye, which have partial zero mobile-money observations. The analytical coding therefore preserves the observed indicator structure of the source panel and distinguishes standalone mobile-money visibility from broader digital-finance activity.

This treatment differs from mean or regression imputation. Mean imputation would assign mobile-money activity to economies where that channel is not separately reported, while regression imputation would infer values from other variables and could blur the distinction between mobile-money-led and bank-led financial architectures. The coding follows the logic of structural missingness and structural zeros for the specific standalone mobile-money indicator being measured: when the missingness mechanism is tied to the non-observation or structural absence of that channel, the assigned zero represents absence of visibility for that reported mobile-money channel rather than absence of broader digital finance (Little & Rubin, 2019; Nardo et al., 2008). For a given mobile-money indicator j in country i and year t , the raw analytical value before standardization is defined as follows:

$$X_{ijt} = \begin{cases} x_{ijt}, & \text{if an empirical mobile-money value is reported,} \\ 0, & \text{if the standalone mobile-money indicator is zero-visible in the source panel.} \end{cases} \quad (3)$$

The resulting X_{ijt} values are then standardized using the same Z-score transformation applied to the other indicators:

$$Z_{ijt} = \frac{X_{ijt} - \mu_j}{\sigma_j}. \quad (4)$$

This procedure makes the diagnostic interpretation transparent while preserving the balanced-panel structure required for the PCA score. Zero-visible mobile-money observations reduce the mobile-money component of the PCA-based DFI score, but they are interpreted as indicator-visibility signals rather than as direct evidence that digital finance is absent. Consequently, the classification of possible bank-led under-observation candidates is presented as a conservative diagnostic result that requires external payment-system data for full validation.

The methodological framework is designed for measurement diagnosis. Its depth comes from triangulating five complementary views of the same measurement object: aggregate trend analysis, dispersion analysis, rank-memory analysis, channel decomposition, and internal sensitivity analysis of the constructed score. This design is appropriate because the available data are strongest for analyzing the observability structure of the existing score. The framework therefore tests the empirically supported question of whether the observed score is more directly visible through the mobile-money indicators than through the available bank-led proxy.

3.2. Channel Visibility Decomposition

For each country in the latest year, the six indicators are standardized across the 40-country sample. Let Z_{ij} denote the standardized value of indicator j for country i . The bank-led digital visibility proxy is defined as:

$$B_i = \frac{1}{2}(Z_{i,Internet} + Z_{i,ATM}). \quad (5)$$

The mobile-money visibility proxy is defined as:

$$M_i = \frac{1}{4}(Z_{i,Agents} + Z_{i,Accounts} + Z_{i,Transactions} + Z_{i,ValueGDP}). \quad (6)$$

The channel-observation gap is then:

$$COG_i = B_i - M_i. \quad (7)$$

A positive COG_i indicates that country i is more visible through the available bank-led proxy than through mobile-money indicators. A negative COG_i indicates that mobile-money visibility exceeds the available bank-led proxy. The COG_i measure functions as a channel-diagnostic companion to DFI_{it} by identifying whether the observed score is shaped by differences in indicator observability. Its interpretation is restricted to relative visibility within the available six-indicator framework.

3.3. Bank-Led Under-Observation Diagnostic

In this study, we apply transparent distributional thresholds to classify countries into diagnostic channel-observability groups. We classify a country as a possible bank-led under-observation candidate when it satisfies three operational conditions: its bank-led proxy lies in the upper quartile, its mobile-money visibility is at or below the median, and its channel-observation gap lies in the upper quartile. The quartile and median thresholds are used as reproducible screening rules for the 40-country sample. The upper quartile identifies countries in the highest 25% of the sample for the relevant diagnostic dimension, while the median separates countries with above-sample and below-sample mobile-money visibility. This threshold design avoids arbitrary country-by-country selection, avoids imposing a normal-distribution assumption, and allows the classification procedure to be replicated. The rule is intentionally conservative because a possible bank-led under-observation candidate must simultaneously show strong bank-led proxy visibility, lower or moderate mobile-money visibility, and a large positive channel-observation gap. The resulting groups are therefore interpreted as diagnostic categories rather than as naturally distinct country types (Nardo et al., 2008). We classify countries in the upper quartile of mobile-money visibility as mobile-money visible. We classify countries below the median on both proxies as structurally low-observed inclusion cases. The remaining countries are treated as hybrid or transitional cases. This rule-based classification keeps the diagnostic

logic auditable and reproducible while identifying cases that warrant closer channel-level interpretation.

3.4. Machine-Learning Sensitivity Analysis

To examine which included indicators most strongly explain the existing DFI score, a Random Forest regressor is estimated using the six original indicators as inputs and the existing $DFI_{i,2024}$ as the outcome. Because the predictors correspond to the same variables used to construct the score, the model functions as a bounded internal sensitivity audit of the indicator system. Its role is internal sensitivity assessment rather than external validation or independent bias evidence. The audit shows which components of the constructed score carry the largest predictive importance within the existing measurement design. K-means clustering is also applied to the channel diagnostics using B_i , M_i , COG_i , zero-count mobile-money variables, and the DFI score. Cluster validity is assessed using the silhouette score to support the transparency of the visual grouping.

4. Results

4.1. Overall DFI Trend and Dispersion

The OIC-wide mean DFI score increased from 11.31 in 2015 to 31.24 in 2024, while the median also moved upward over the same period. Figure 1 reports the mean and median trajectories. The figure is included to establish the first empirical baseline: the observed DFI score improved over time for the OIC sample as a whole. This indicates that the later discussion of channel observability is linked to the distribution of improvement and to the channels through which digital finance is most visible in the indicator set.

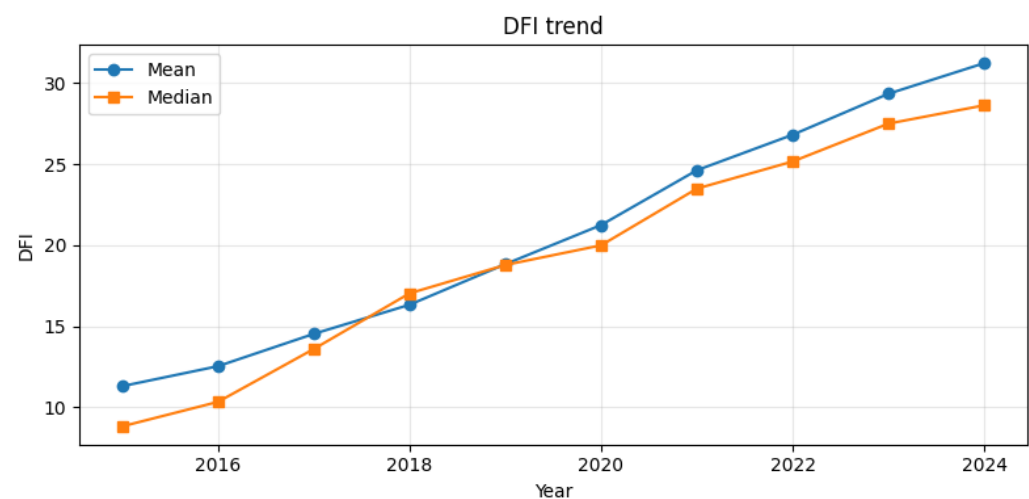


Figure 1. DFI mean and median trend for 40 OIC countries, 2015–2024. The vertical axis reports the DFI score on the 0–100 scale. The mean and median lines show aggregate improvement in observed digital financial inclusion over the study period. The gap between the mean and median also provides an initial indication of distributional asymmetry.

Aggregate improvement coexists with divergence. Figure 2 shows that the standard deviation of DFI scores increased from 9.18 in 2015 to 20.54 in 2024, and the P90–P10 gap increased from 23.05 to 47.37. This figure is necessary because a rising average can conceal widening cross-country inequality. The result shows that the region experienced improvement without convergence: some countries accelerated sharply, while others remained far below the observed leaders.

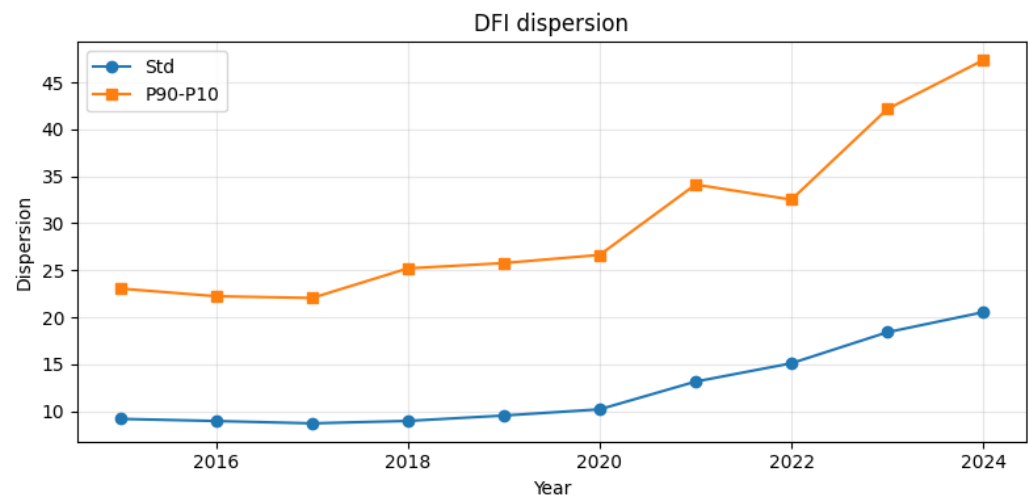


Figure 2. DFI dispersion over time. The figure reports the standard deviations of DFI scores and the P90–P10 gap for each year. Both indicators rise over the period, showing that OIC countries become more unequal in observed DFI despite aggregate improvement. P90–P10 denotes the difference between the 90th and 10th percentile country scores.

4.2. Rank-Memory Decay and Leadership Replacement

The 2015 top-ten countries and the 2024 top-ten countries have no overlap. The 2015 leading group consists mainly of relatively advanced or early-infrastructure countries, whereas the 2024 leading group consists mainly of mobile-money-intensive economies. Figure 3 reports the rank correlation between each year's DFI ranking and the 2015 ranking. The decline shows that the initial hierarchy lost explanatory power over time.

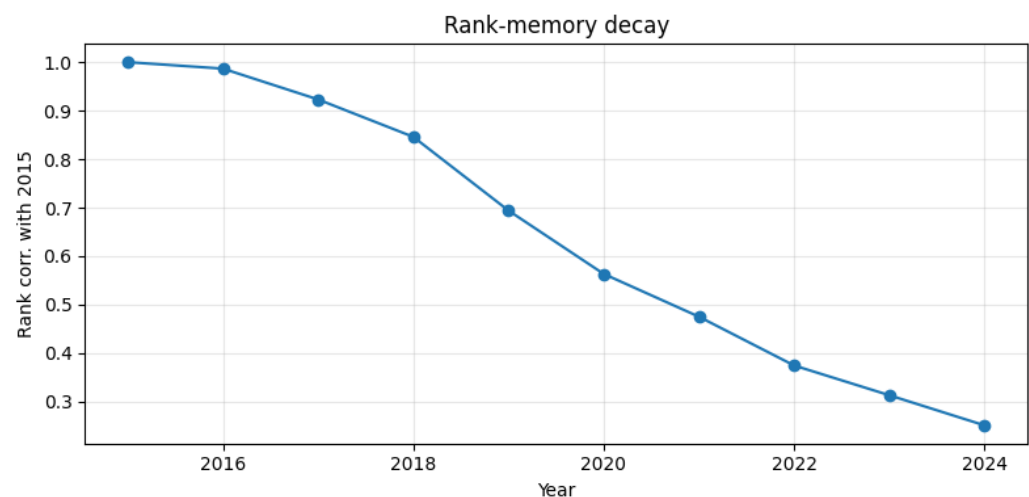


Figure 3. Rank-memory decay in DFI rankings. The figure plots the rank correlation between each annual country ranking and the 2015 ranking. A lower value indicates that the initial hierarchy is less predictive of the later ranking. The downward movement supports the interpretation of long-run leadership replacement rather than persistence of the initial observed DFI hierarchy.

This result is relevant to the channel-observability interpretation because leadership replacement extends beyond a movement from lower income to higher income or from less-developed to more-developed physical infrastructure. It is consistent with a shift toward countries whose digital financial activity is highly visible through mobile-money indicators.

4.3. Channel-Observation Structure

Figure 4 plots countries according to bank-led digital visibility and mobile-money visibility. Countries in the lower-right area, including Türkiye, Qatar, Saudi Arabia, the United Arab Emirates, Malaysia, Bahrain, and Jordan, show strong bank-led visibility but lower mobile-money visibility. Countries in the upper-left or upper-middle area, including Senegal, Benin, Nigeria, Côte d'Ivoire, Guinea-Bissau, Burkina Faso, Guinea, Mali, Mozambique, and Togo, are strongly visible through mobile-money indicators.

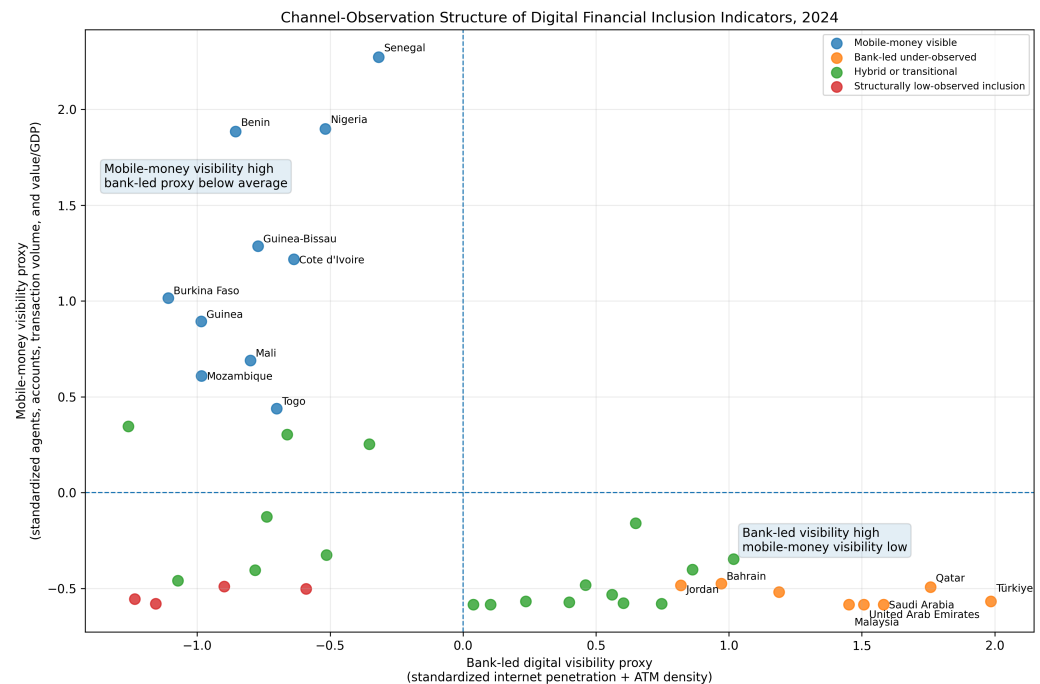


Figure 4. Channel-observation structure of DFI indicators in 2024. The horizontal axis represents the standardized bank-led digital visibility proxy calculated from internet penetration and ATM density. The vertical axis represents the standardized mobile-money visibility proxy, calculated from mobile agents, mobile accounts, mobile transaction volume, and mobile transaction value relative to GDP. Dashed reference lines mark zero, the sample average after standardization. Countries in the lower-right region show strong bank-led visibility but lower mobile-money visibility, which is consistent with possible under-observation in a mobile-money-heavy indicator set. Countries in the upper region are highly visible through mobile-money indicators.

Figure 4 provides the central channel-level diagnostic for the 2024 cross-section. It shows that countries are visible through different indicator channels within the available dataset: some are observed mainly through mobile-money variables, while others are observed mainly through the bank-led infrastructure proxy. This distributional pattern is consistent with asymmetric channel observability and supports the interpretation that DFI rankings should be read together with the channel structure behind the score.

4.4. Bank-Led Under-Observation Candidates

Table 2 lists the main possible bank-led under-observation candidates in 2024. Türkiye has the highest bank-led proxy rank but is ranked 11th in the DFI score. Qatar, Saudi Arabia, the United Arab Emirates, and Malaysia also rank highly in the bank-led proxy but lower in the DFI ranking. Saudi Arabia, the United Arab Emirates, and Malaysia each have four zero mobile-money variables, meaning that the dataset records no separately reported standalone mobile-money activity for these indicators. These zero values refer specifically to the mobile-money variables and are analytically distinct from broader digital banking, card, POS, QR, or instant-payment services. The table therefore identifies cases

where the observed DFI rank should be interpreted through the channel structure of the available variables.

Table 2. Top bank-led under-observation candidates, 2024. The table ranks countries with high bank-led visibility relative to mobile-money visibility. DFI rank refers to the position in the existing 2024 DFI score, while bank proxy rank refers to the position based only on the bank-led visibility proxy. A larger positive channel gap indicates that bank-led visibility exceeds mobile-money visibility.

Country	DFI Rank	Bank Proxy Rank	Channel Gap	Zero Mobile-Money Variables
Türkiye	11	1	2.552	1
Qatar	12	2	2.251	0
Saudi Arabia	16	3	2.165	4
United Arab Emirates	18	4	2.091	4
Malaysia	20	5	2.035	4
Maldives	22	6	1.707	0
Bahrain	21	8	1.445	2
Albania	17	7	1.364	0
Morocco	25	11	1.326	2
Jordan	23	10	1.303	0

Note: Zero mobile-money variables count how many of the four mobile-money indicators are recorded as zero in the dataset. These values are interpreted as mobile-money visibility signals and should be distinguished from broader digital banking, card, POS, QR, or instant-payment activity.

Figure 5 visualizes the same channel-observation gap. The figure makes the rank-gap pattern transparent and shows that possible under-observation is distributed across several countries rather than concentrated in a single case. These cases are interpreted as diagnostic candidates because direct measures of online banking, card payments, POS payments, QR payments, or instant-payment usage are outside the balanced panel.

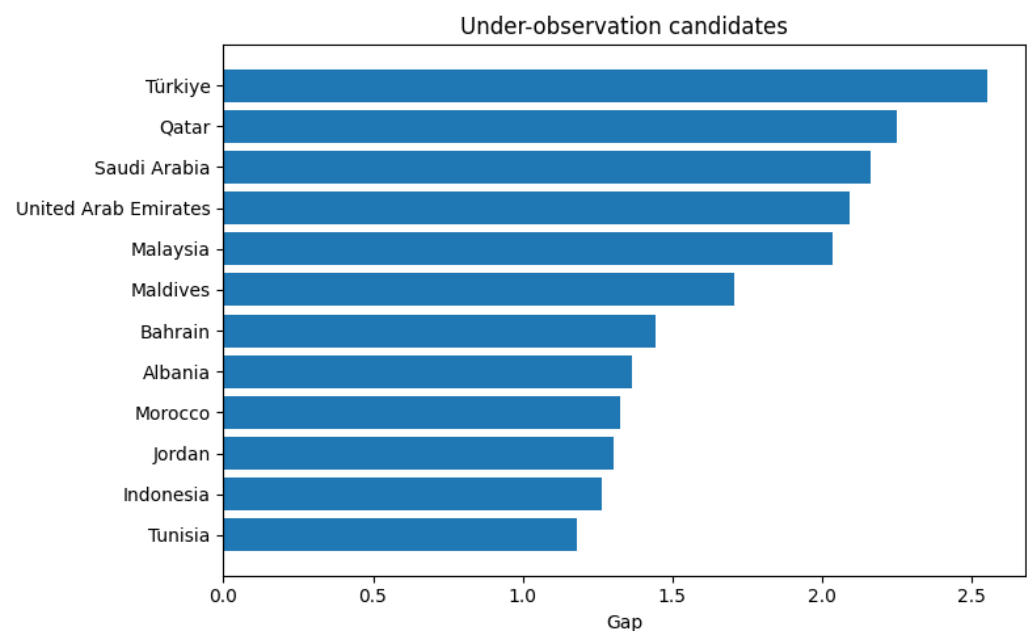


Figure 5. Countries most exposed to possible bank-led under-observation. The horizontal axis reports the channel-observation gap, defined as bank-led digital visibility minus mobile-money visibility. Higher values indicate stronger bank-led visibility relative to mobile-money visibility. The figure visually supports Table 2 by showing that the possible under-observation concern appears across several countries, not only one case.

4.5. Mobile-Money Visibility Advantage

Table 3 and Figure 6 show the countries most visible through mobile-money indicators. Senegal ranks first in the DFI score and first in mobile-money visibility. Nigeria, Benin, Guinea-Bissau, Côte d'Ivoire, Burkina Faso, Guinea, Mali, Mozambique, and Togo also occupy the top mobile-money visibility group. These results show that the leading 2024 DFI rankings coincide with strong visibility through mobile-money access and usage variables. The interpretation is therefore channel-specific: these countries are highly visible through the mobile-money variables included in the score.

Table 3. Top mobile-money-visible countries, 2024. The table reports the countries whose digital financial inclusion is most directly observed through mobile-money indicators. Mobile-money visibility is the standardized average of mobile agents, mobile accounts, mobile transaction volume, and mobile transaction value relative to GDP.

Country	DFI Rank	Mobile-Money Visibility	DFI Score
Senegal	1	2.273	100.00
Nigeria	3	1.899	64.60
Benin	2	1.885	80.55
Guinea-Bissau	5	1.287	57.60
Côte d'Ivoire	4	1.218	61.17
Burkina Faso	6	1.016	53.74
Guinea	7	0.893	48.95
Mali	8	0.691	46.20
Mozambique	9	0.610	42.37
Togo	10	0.439	37.75

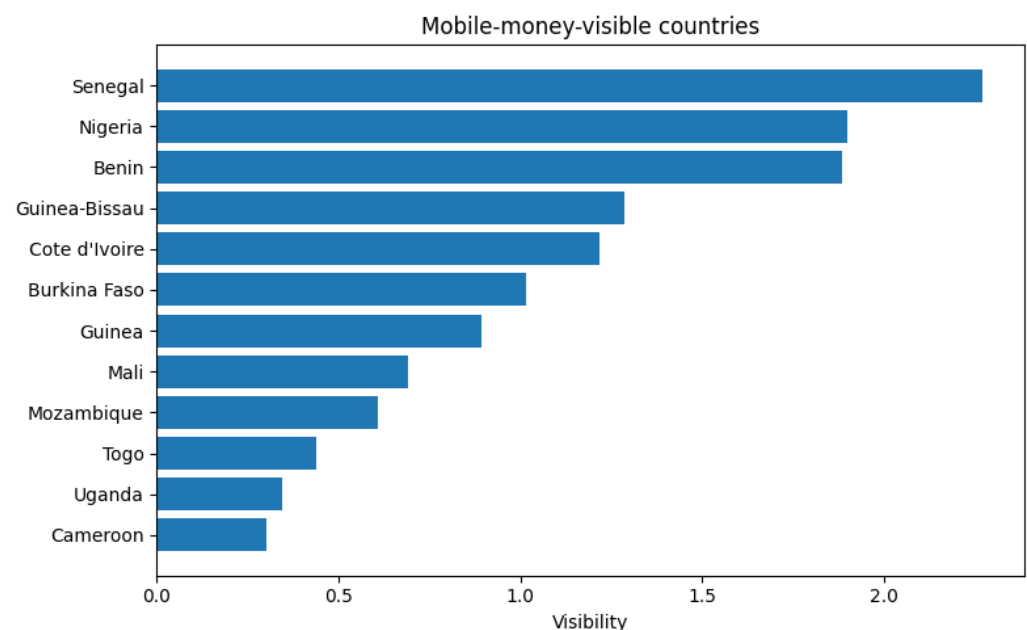


Figure 6. Countries most visible through mobile-money indicators. The horizontal axis reports the mobile-money visibility proxy. The leading countries in the 2024 DFI ranking are also highly visible through mobile-money access and usage variables, indicating that the existing indicator set strongly captures mobile-money-led inclusion.

The result should be interpreted positively for mobile-money economies. It indicates that the selected DFI indicators are particularly effective at observing digital finance where mobile money is the dominant inclusion channel. The measurement issue arises when

the same mobile-money-heavy structure is used to compare such countries with bank-led economies whose digital-finance activity is organized differently.

4.6. Machine-Learning Sensitivity of the Existing DFI Score

The Random Forest sensitivity audit shows that the existing DFI score is most strongly associated with mobile-money usage indicators within the same six-variable indicator system from which the score was constructed. Mobile transactions per 1000 adults has the highest importance score (0.386), followed by transaction value/GDP (0.242). ATMs per 100,000 adults ranks third (0.120), while internet penetration has the lowest importance (0.056). Table 4 reports the numerical importance values, and Figure 7 provides the corresponding visual comparison. The values are interpreted as within-score sensitivity evidence showing which included indicators most strongly structure the existing DFI ranking.

Table 4. Random Forest variable importance for explaining the existing DFI score. The model uses the six original indicators as predictors and the existing 2024 DFI score as the outcome. The importance values are diagnostic and descriptive, showing within-score sensitivity among the indicators that constitute the existing score.

Indicator	Importance
Mobile transactions per 1000 adults	0.386
Value of mobile-money transactions/GDP	0.242
ATMs per 100,000 adults	0.120
Mobile agents per 100,000 adults	0.106
Mobile accounts per 1000 adults	0.089
Internet penetration	0.056

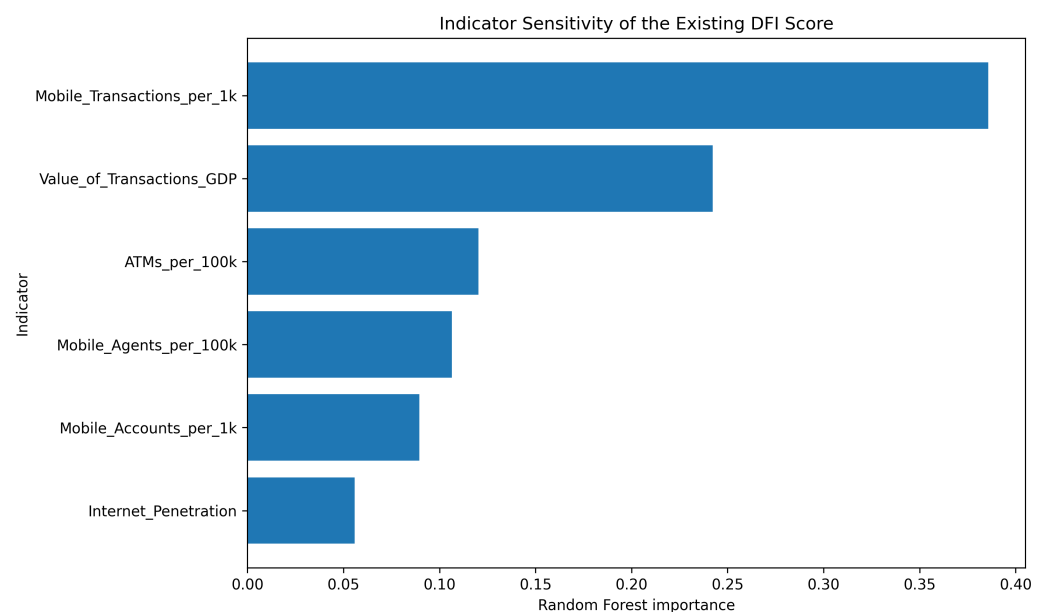


Figure 7. Indicator sensitivity of the existing DFI score. The Random Forest diagnostic shows that the score is most strongly associated with mobile-money transaction volume and transaction value relative to GDP. Because the same six indicators are used as predictors, the figure is interpreted as internal measurement sensitivity within the existing indicator system.

This finding is reported as a transparency check on the internal structure of the existing score. Countries with large, separately reported mobile-money transactions are more directly visible within the existing DFI score because those transactions are explicitly included in the six-variable indicator system. Bank-account-based digital payments, mobile banking, card payments, QR payments, POS transactions, and instant-payment rails require addi-

tional direct variables beyond the balanced panel used here. The incremental contribution of the Random Forest result lies in documenting internal measurement sensitivity within the constructed score, while external validation requires independent digital-banking and payment-system indicators.

5. Discussion

5.1. Reinterpreting Lower Rankings in Financially Advanced Economies

The results require channel-level interpretation. A country such as the United Arab Emirates may appear lower in the 2024 DFI ranking because the available indicator structure records internet penetration and ATM density while recording zero values for the four standalone mobile-money variables. This position reflects the way bank-led digital finance is represented in the balanced panel rather than a direct judgement about the country's broader digital-finance infrastructure. The appropriate interpretation is therefore conditional: the country is less visible in a mobile-money-heavy DFI indicator system while remaining strongly represented through the available bank-led infrastructure variables.

This interpretation also applies to Saudi Arabia, Malaysia, Qatar, Bahrain, Türkiye, Jordan, Albania, Morocco, and other countries with strong bank-led or hybrid financial infrastructures. Their lower observed DFI ranks are best understood through the channel composition of the index rather than as direct evidence of limited digital financial services. They are identified as possible under-observation candidates because stronger interpretation requires direct evidence from mobile banking, card payments, POS payments, QR payments, instant transfers, and related bank-led digital-payment channels.

5.2. Why Mobile-Money Economies Are Highly Visible

The leading 2024 countries, including Senegal, Benin, Nigeria, Côte d'Ivoire, Guinea-Bissau, Burkina Faso, Guinea, Mali, Mozambique, and Togo, are better interpreted through the digital-finance channels captured by the indicator set than through a simple hierarchy of income or general technological advancement. They rank highly because their digital financial inclusion is expressed through channels that the index observes directly: agents, mobile accounts, transaction volume, and transaction value. In such countries, mobile money is not merely an auxiliary payment tool; it is often the central financial inclusion infrastructure.

This should be interpreted positively. Mobile money can produce substantial inclusion gains where conventional banking networks are sparse, costly, or geographically limited. The measurement issue appears when the same mobile-money-heavy indicator structure is used to compare mobile-money-led economies with bank-led economies whose digital-finance activity is organized differently. The analysis therefore clarifies the domain in which mobile-money indicators provide their strongest observability.

5.3. Implications for IMF- and World Bank-Style DFI Measurement

The findings complement IMF-, World Bank-, FAS-, and Findex-style indicators by adding an interpretation layer focused on channel observability. These indicators are essential because they provide internationally comparable data. The results show that comparability should be accompanied by attention to whether digital-finance architectures are observed with similar intensity across countries. A DFI index based on available mobile-money and infrastructure indicators can be internally coherent while requiring channel diagnostics for bank-led digital-finance channels that are represented indirectly in the same dataset.

Future DFI measurement should therefore distinguish between at least two observable architectures: mobile-money-led digital inclusion and bank-led embedded digital finance. Additional indicators should include mobile and internet banking usage, digital card payments, POS payments, instant-payment-system usage, QR payments, digital wallet

transactions connected to bank accounts, and digital government transfers. Including such variables would strengthen cross-country interpretation by separating channel visibility from digital-finance maturity.

5.4. Applicability Beyond the OIC Context

Although the empirical application focuses on 40 OIC countries, the diagnostic logic is transferable to other regional or organizational comparisons where member states have heterogeneous financial architectures. The framework could be applied to groups such as regional development banks, monetary unions, economic communities, or cross-country policy-monitoring exercises when a common DFI score is used to compare mobile-money-led, bank-led, and hybrid financial systems. The transferable element is the procedure: separate the available indicators by channel family, examine whether rankings are dominated by one directly observed architecture, and report the interpretation boundaries when major digital-payment channels are absent from the data.

5.5. Theoretical and Practical Implications

The theoretical implication is that DFI should be treated as an architecture-dependent construct rather than as a single technology-neutral outcome. A composite score may be statistically coherent and internationally comparable while still requiring channel-level interpretation when the included indicators observe one institutional channel more directly than another. This matters for financial inclusion theory because access, adoption, and usage are mediated by the infrastructure through which services are delivered. Mobile-money-led inclusion, bank-led digital inclusion, and hybrid payment ecosystems may produce similar user-facing outcomes while leaving different traces in international datasets.

The practical implication is that policymakers, regulators, and development institutions should interpret DFI rankings together with channel diagnostics. For mobile-money-led economies, high visibility in the score may correctly reflect the central role of agents, accounts, and mobile transactions. For bank-led or hybrid economies, lower visibility in mobile-money indicators should be interpreted through the architecture of the indicator set and the availability of direct bank-led digital-payment variables. Statistical agencies and international data providers should therefore expand harmonized reporting on mobile banking, internet banking, card payments, POS usage, QR payments, instant transfers, and bank-linked digital wallets when comparable data become available.

5.6. Limitations, External Validation Boundary, and Future Research

The principal data boundary of this study is the availability of balanced annual information on direct bank-led digital-finance indicators. A consistent longitudinal panel for 40 heterogeneous OIC countries over 2015–2024 requires continuous annual data for every country-year observation. Direct metrics that capture embedded digital banking—including online banking usage, mobile banking transactions, card-payment volumes, POS transactions, QR-code payments, instant-payment-system activity, and bank-linked wallet usage—remain unevenly reported across this cross-country sample and period. Consequently, the bank-led proxy based on internet penetration and ATM density represents the observable infrastructure component of bank-led digital finance within the available annual panel.

External validation requires harmonized annual indicators that directly measure the bank-led and payment-system channels represented only indirectly in the present panel. Relevant validation indicators include mobile banking users or transactions, internet banking transactions, card-payment values, POS transaction density, QR-payment adoption, instant-payment usage, fintech wallet transactions, and digital government-payment flows for the same 40 countries and the same 2015–2024 period. Current international data sources

provide valuable but uneven coverage for this purpose. The World Bank Global Findex offers strong demand-side evidence on account use, digital payments, card ownership, and related financial inclusion behavior, yet its survey-wave structure differs from a continuous annual country panel (Demirguc-Kunt et al., 2018, 2022; World Bank, 2025). The IMF Financial Access Survey provides annual supply-side financial access data, while the completeness and harmonization of direct mobile and internet banking variables vary across the 40 OIC countries during 2015–2024 (IMF, 2017, 2025). National payment-system statistics add further detail on cards, POS, QR payments, and instant payments, although definitions, institutional coverage, and public availability differ across countries.

Within this data environment, the empirical results should be interpreted as channel-observability diagnostics. The lower DFI rankings of possible bank-led under-observation candidates indicate potential under-observation within the available indicator framework and should be read together with the channel composition of the score. Future research should reconstruct DFI indices using direct digital-payment and digital-banking variables once statistical agencies, central banks, and international databases provide harmonized continuous data for these channels. A stronger validation framework should compare the existing DFI score with indicators such as mobile banking users, internet banking transactions, card payment values, POS transaction density, instant-payment usage, QR payment adoption, fintech wallet usage, and digital government-payment flows. Future studies should also conduct sensitivity analysis using alternative missing-data treatments, alternative threshold rules, alternative weighting methods, and separate models for bank-led, mobile-money-led, and hybrid financial systems.

5.7. Policy Implications for OIC Countries

For mobile-money-visible countries, the policy priority is to sustain inclusive expansion while strengthening interoperability, consumer protection, cybersecurity, agent liquidity, competition, and regulatory supervision. For possible bank-led under-observation candidates, the priority is to improve measurement and ensure that bank-led digital finance reaches excluded groups, including low-income households, migrants, rural users, women, and small firms, rather than to assume that standalone mobile-money systems are the appropriate policy pathway in every context. For structurally low-observed countries, the challenge remains broader: internet access, institutional capacity, payment infrastructure, and basic financial access must improve together.

The OIC context is therefore better understood as a heterogeneous group of financial architectures than as a single digital-inclusion ladder. A policy framework that works in mobile-money-led West African economies may be less appropriate for GCC or high-income bank-led economies. The same DFI score can have different meanings depending on the channel structure behind it. This is the central policy implication of the channel-observability analysis.

6. Conclusions

This paper examined channel observability as a measurement-interpretation issue in digital financial inclusion analysis. Using an existing DFI index for 40 OIC countries from 2015 to 2024, the study showed that aggregate digital financial inclusion improved, dispersion widened, and the ranking hierarchy changed substantially. The channel-decomposition results indicate that countries with strong mobile-money visibility are highly visible in the 2024 DFI ranking, while several countries with strong values on the bank-led infrastructure proxy show lower mobile-money visibility.

Taken together, the findings support an architecture-sensitive interpretation of DFI rankings. Digital finance reported through mobile-money agents, accounts, transaction

volume, and transaction value is observed more directly than digital finance embedded in bank accounts, mobile banking applications, card systems, POS networks, QR payments, instant-payment rails, and related infrastructures that lie outside the available indicator set. Lower DFI rankings in bank-led economies should therefore be read as channel-observability outcomes within the available data rather than as mechanical evidence of lower overall digital-finance maturity. The results identify an interpretation boundary of the existing score and motivate external validation using direct digital-banking and payment-system indicators.

The contribution of this paper is a channel-observability diagnostic for interpreting an existing DFI score. It shows how internationally comparable DFI rankings can depend on the observability of different digital-finance channels and how indicator composition affects the reading of country positions. The principal data boundary concerns the uneven availability of direct indicators on mobile banking, online banking, card payments, POS usage, instant payments, QR transactions, fintech wallet usage, and public digital-payment infrastructures in a balanced annual 2015–2024 panel. Future research should integrate such variables, report exact source series, test alternative zero-coding and missing-data treatments, test alternative threshold rules, and develop more symmetric DFI measurement frameworks for countries with heterogeneous financial architectures.

Author Contributions: N.A.-H.: Conceptualization; Methodology; Formal analysis; Investigation; Resources; Validation; Project administration; Writing—original draft. A.L.S.A.-K.: Conceptualization; Methodology; Software; Data curation; Formal analysis; Investigation; Resources; Validation; Visualization; Project administration; Writing—original draft; Writing—review and editing. H.A.: Supervision; Validation; Project administration; Writing—review and editing. E.U.: Methodology; Validation; Writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The cleaned and imputed panel dataset and the derived diagnostic outputs are available from the corresponding author upon reasonable request. Raw variables were compiled from internationally available financial inclusion and financial access data sources, including the IMF Financial Access Survey and World Bank data sources.

Acknowledgments: The authors acknowledge Istanbul Aydin University for institutional support. During the preparation of this manuscript, Python 3.13.5 libraries including pandas, NumPy, scikit-learn, and Matplotlib were used for data processing, diagnostic analysis, and figure generation. The authors reviewed and edited all computational outputs and take full responsibility for the content of this publication.

Conflicts of Interest: Ahmed Lateef Salih Al-Karawi was employed by Defne Telekomünikasyon A.Ş.. The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DFI	Digital Financial Inclusion
OIC	Organisation of Islamic Cooperation
IMF	International Monetary Fund
FAS	Financial Access Survey

PCA	Principal Component Analysis
GDP	Gross Domestic Product
ATM	Automated Teller Machine
POS	Point of Sale
QR	Quick Response
GCC	Gulf Cooperation Council
COG	Channel-Observation Gap

References

- Aker, J. C., & Mbiti, I. M. (2010). Mobile phones and economic development in Africa. *Journal of Economic Perspectives*, 24(3), 207–232. [CrossRef]
- Beck, T., Demirguc-Kunt, A., & Levine, R. (2007). Finance, inequality and the poor. *Journal of Economic Growth*, 12, 27–49. [CrossRef]
- Camara, N., & Tuesta, D. (2014). *Measuring financial inclusion: A multidimensional index* (Working Paper No. 14/26). BBVA Research. Available online: https://www.bbva.com/wp-content/uploads/2014/09/WP14-26_Financial-Inclusion2.pdf (accessed on 14 June 2026).
- Demir, A., Pesqué-Cela, V., Altunbas, Y., & Murinde, V. (2022). Fintech, financial inclusion and income inequality: A quantile regression approach. *The European Journal of Finance*, 28(1), 86–107. [CrossRef]
- Demirguc-Kunt, A., & Klapper, L. (2013). Measuring financial inclusion: Explaining variation in use of financial services across and within countries. *Brookings Papers on Economic Activity*, 2013, 279–340. [CrossRef]
- Demirguc-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2022). *The global finindex database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19*. World Bank. [CrossRef]
- Demirguc-Kunt, A., Klapper, L., Singer, D., Ansar, S., & Hess, J. (2018). *The global finindex database 2017: Measuring financial inclusion and the fintech revolution*. World Bank. [CrossRef]
- Filmer, D., & Pritchett, L. H. (2001). Estimating wealth effects without expenditure data: An application to educational enrollments in states of India. *Demography*, 38(1), 115–132. [CrossRef] [PubMed]
- Gomber, P., Koch, J.-A., & Siering, M. (2017). Digital finance and FinTech: Current research and future research directions. *Journal of Business Economics*, 87, 537–580. [CrossRef]
- International Monetary Fund. (2017). *Financial access survey guidelines and manual*. International Monetary Fund. Available online: <https://data.imf.org/en/datasets/IMF.STA:FAS> (accessed on 14 June 2026).
- International Monetary Fund. (2025). *Financial access survey 2025 annual report*. International Monetary Fund. Available online: <https://data.imf.org/-/media/iData/External-Storage/Documents/7FC05452C6C743D2BFB6188D2E248A38/en/2025-FAS-Annual-Report.pdf> (accessed on 14 June 2026).
- Jack, W., & Suri, T. (2011). *Mobile money: The economics of M-PESA* (NBER Working Paper 16721). National Bureau of Economic Research. [CrossRef]
- Jack, W., & Suri, T. (2014). Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. *American Economic Review*, 104(1), 183–223. [CrossRef]
- Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement*, 20(1), 141–151. [CrossRef]
- Khera, P., Ng, S., Ogawa, S., & Sahay, R. (2021a). *Is digital financial inclusion unlocking growth?* (IMF Working Paper No. 21/167). International Monetary Fund. Available online: <https://www.imf.org/en/publications/wp/issues/2021/06/11/is-digital-financial-inclusion-unlocking-growth-460738> (accessed on 14 June 2026).
- Khera, P., Ng, S., Ogawa, S., & Sahay, R. (2021b). *Measuring digital financial inclusion in emerging market and developing economies: A new index* (IMF Working Paper No. 21/90). International Monetary Fund. Available online: <https://www.imf.org/-/media/files/publications/wp/2021/english/wp2021090-print-pdf.pdf> (accessed on 14 June 2026).
- Klapper, L., El-Zoghbi, M., & Hess, J. (2016). *Achieving the sustainable development goals: The role of financial inclusion*. CGAP. Available online: https://www.cgap.org/sites/default/files/Working-Paper-Achieving-Sustainable-Development-Goals-Apr-2016_0.pdf (accessed on 14 June 2026).
- Kouladoun, J. C., Wirajing, M. A. K., & Nchofoung, T. N. (2022). Digital technologies and financial inclusion in Sub-Saharan Africa. *Telecommunications Policy*, 46(9), 102387. [CrossRef]
- Little, R. J. A., & Rubin, D. B. (2019). *Statistical analysis with missing data* (3rd ed.). John Wiley & Sons. [CrossRef]
- Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffmann, A., & Giovannini, E. (2008). *Handbook on constructing composite indicators: Methodology and user guide*. OECD Publishing. [CrossRef]
- Ozili, P. K. (2018). Impact of digital finance on financial inclusion and stability. *Borsa Istanbul Review*, 18(4), 329–340. [CrossRef]

- Sarma, M. (2008). *Index of financial inclusion* (Working Paper No. 215). Indian Council for Research on International Economic Relations. Available online: https://icrier.org/pdf/Working_Paper_215.pdf (accessed on 14 June 2026).
- Sarma, M., & Pais, J. (2011). Financial inclusion and development. *Journal of International Development*, 23(5), 613–628. [CrossRef]
- Suri, T. (2017). Mobile money. *Annual Review of Economics*, 9, 497–520. [CrossRef]
- Suri, T., & Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science*, 354(6317), 1288–1292. [CrossRef] [PubMed]
- Svirydzenka, K. (2016). *Introducing a new broad-based index of financial development* (IMF Working Paper No. 16/5). International Monetary Fund. Available online: <https://www.imf.org/en/publications/wp/issues/2016/12/31/introducing-a-new-broad-based-index-of-financial-development-43621> (accessed on 14 June 2026).
- World Bank. (2025). *The global finindex database 2025: Connectivity and financial inclusion in the digital economy*. World Bank. [CrossRef]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.