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A Multidimensional Financial Inclusion Index for Ethiopia

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Abstract

This study develops a multi-dimensional composite index to measure financial inclusion in Ethiopia, using a two-stage Principal Component Analysis based on ten traditional and five digital indicators from 2015 to 2023. The results reveal a significant increase in Ethiopia's financial inclusion score, rising from an average of 10.89% in 2015 to 52.18% in 2023. Among the dimensions, traditional availability (0.2625) is the most influential, followed by traditional usage (0.2616), digital accessibility (0.2505), and digital availability (0.2254). Further analysis reveals that the Commercial Bank of Ethiopia alone contributes 48.99% for financial inclusion score, while five medium-sized and eleven small-sized private banks collectively account for 29.26% and 21.75%, respectively. The developed index proves to be a valuable tool for policy-making and evaluation, addressing previous limitations like arbitrary weight selection. It offers a detailed perspective on financial inclusion trends among commercial banks in Ethiopia, consistent with existing studies.

Keywords: Financial inclusion; Multidimensional composite index; Principal component analysis; Ethiopia's commercial banks

JEL classification: G2; G2; C43; G21.

1. Introduction

Recent studies indicate that financial inclusion (FI) has become a key policy priority in many countries (Dabla-Norris et al., 2021; Ozili, 2021c; Vo et al., 2021). While definitions of FI vary by socio-economic context (Aduda & Kalunda, 2012; Akileng et al., 2018; Ahamed & Mallick, 2019), it generally refers to providing accessible, timely, adequate, and affordable financial services to all legal entities, especially marginalized communities (Sarma, 2008; De Koker & Jentzsch, 2013).

Having access to financial services is essential for creating economic opportunities, as it allows for savings, investments, and credit access (Subbarao, 2009). Studies show that FI promotes economic growth (Van et al., 2021; Kim et al., 2018; Levine, 2005), greater financial stability (Arebo et al., 2024; Elsayed 2020; Vo et al., 2021), enhance education (Demirgüç-Kunt & Levine, 2009), financial protection (Ozili, 2021b; Elsayed 2020), increase financial performance (Shihadeh et al., 2018; Sha'ban et al., 2020; and Issaka et al., 2020), decrease poverty (Niaz, 2022; Tran & Le, 2021; Koomson et al., 2020; Omar & Inaba, 2020; Bruhn & Love 2014; Inoue & Hamori, 2012), reduce income inequality (Huang & Zhang, 2019; Omar & Inaba, 2020; Park & Mercado, 2018; Demirgüç-Kunt & Levine, 2009), encourage gender equality (Ohiomu & Ogbeide-Osaretin, 2019; Staveren, 2001).

Recognizing the critical role FI plays in the country's development, Ethiopia's government implemented a National Financial Inclusion Strategy (NFIS) in two stages. The first phase ran from 2015 to 2021, followed by the current phase which began in 2021 and extends to 2025, with the aim of increasing the adult population's access to formal financial services to 70% (NFIS, 2021). Despite efforts, the 2018/2019 Ethiopian Socioeconomic Survey (ESS) shows that only 30.5% of adults have bank accounts, below the African average of 35% and the global average of 61.5% (CSA et al., 2021). The primary barriers identified under the survey include insufficient funds (36.3%), lack of perceived reasons (15.2%), limited understanding of the benefits of owning an account (12.3%), excessive distance to the nearest financial institution (10.9%), and lack of knowledge about account opening procedures (10.7%) (CSA et al., 2021).

Given the relatively low rate of bank account ownership in Ethiopia, which stands at 30.5% (CSA et al., 2021), the study opts for FI as a solution to address financial exclusion. The primary goal of FI is to enable the most disadvantaged populations to access basic financial services at a low cost (Aymar & Fabrice-Gilles, 2021; Hannig & Jensen, 2010; Dabla-Norris et al., 2015). Digital finance, in particular, presents a compelling opportunity to engage individuals who are traditionally excluded from the formal financial system due to geographical, economic, or social barriers (Ozili, 2021b). The rise of digital platforms and mobile banking has been highlighted as a key driver in advancing financial inclusiveness (Aymar & Fabrice-Gilles, 2021; Senou et al., 2019). However, digital financial inclusion (DFI) cannot entirely replace traditional financial inclusion (TFI). While DFI primarily caters to small-scale financial transactions and loans (Mhlanga, 2020), TFI is often preferred for larger capital needs and more complex financial products. Therefore, DFI and TFI are complementary and mutually dependent, each serving different aspects of financial needs (Mao et al., 2023).

Measuring FI is the first step towards raising awareness about the importance of FI (Sarma, 2016). It is crucial for assessing the impact of stakeholder initiatives and strategizing future actions (Nguyen, 2021). As Gharbi & Kammoun (2023) aptly highlight, a multidimensional FI measure fosters a deeper understanding of its relationship with other relevant macroeconomic variables. However, current approaches employed in Ethiopia primarily rely on micro-level or unidimensional indicators, which restrict a comprehensive understanding of FI. Sarma (2008) underscores that relying on a single indicator to assess the extent and impact of FI can be misleading. Therefore, this study aims to develop a multidimensional FI measurement index to address this critical gap. The proposed index will incorporate both demand-side and supply-side aspects, providing a nuanced and holistic understanding of FI in Ethiopia. Additionally, this study introduces digital indicators to measure FI that have been overlooked in previous studies. To achieve this, the study employs a two-stage Principal Component Analysis (PCA) approach to construct the first comprehensive FI index for Ethiopia (2015-2023), covering both TFI and DFI dimensions.

The next subsequent part of this paper is organized as follows. The next part presents an overview of the previous studies that measure FI. Part 3 describes methodology. Subsequently, Part 4 presents the obtained result. Finally, Part 5 provides conclusion and recommendations for stakeholders.

2. Measurement of financial inclusion

Composite indices enable cross-temporal and cross-spatial comparisons, prompting the need for dimensionality reduction techniques (OECD, 2008). These indices aim to capture multifaceted concepts, encompassing a multitude of indicators under a single, holistic metric (Mishra, 2007). The literature on FI measurement employs parametric, non-parametric, and hybrid techniques (Gharbi & Kammoun, 2023; Nizam et al., 2020; Ahamed & Mallick, 2019; Nuzzo & Piermattei, 2019; Camara & Tuesta, 2017). Using statistical models, studies under parametric methods in FI research calculate weights based on inherent indicator covariation (Nguyen, 2021; Sha'ban et al., 2020; Le et al., 2019; Park & Mercado, 2018). Conversely, studies employing non-parametric methods assign weights based on expert intuition (Chakravarty & Pal, 2013; Sarma, 2008), albeit the yearly changes in the data (Decancq & Lugo, 2013) and weights potentially being assigned prior to data collection (Chen et al., 2019). Hybrid methods, applied in some studies (Van et al., 2021; Nizam et al., 2020), combine parametric and non-parametric techniques, but lack standardized methodologies and theoretical foundations. Table A4 summarizes selected previous empirical work on the development of a FI.

2.1 Application of principal component analysis

PCA is a cornerstone of modern data analysis, widely applied across scientific disciplines for its capacity to reduce dimensionality and extract key patterns from multivariate datasets (Kurita, 2019; Abdi & Williams, 2010). Originally introduced by Pearson (1901) and advanced by Hotelling (1933), PCA remained underutilized until the proliferation of electronic computing, which facilitated its integration into statistical software packages and cemented its role as a fundamental multivariate statistical method (Mishra et al., 2017; Jolliffe & Cadima, 2016; Maćkiewicz & Ratajczak, 1993). At its core, PCA transforms a dataset of interrelated variables into a smaller set of uncorrelated variables known as principal components (PCs). These PCs are ordered by the amount of variance they capture, with the first component explaining the greatest share of the total variation. By retaining only the most significant components, PCA reduces the dataset's dimensionality while preserving as much of its informational content as possible (Greenacre et al., 2022). This process enables researchers to distill the essence of high-dimensional data into a more manageable form.

The application of PCA is particularly critical in scenarios involving large, multivariate datasets, where redundancy among variables can impede analysis. High-dimensional data often pose challenges such as multicollinearity, computational inefficiency, and diminished clarity in visualization and interpretation. PCA addresses these issues by systematically removing redundancy while minimizing information loss, enabling clear and actionable insights (Mavungu, 2023). In the financial domain, PCA has emerged as an indispensable tool within the broader field of financial data science. Its precision, efficiency, and cost-effectiveness make it highly suitable for analyzing structured and unstructured financial data (Janićijević et al., 2022). Recent studies have applied PCA to address diverse challenges, including financial risk assessment (Mavungu, 2023; Hamdy & Hussei, 2016), financial reporting (Robu & Istrate, 2015; Li & Zhang, 2011), customer analytics (Bandyopadhyay et al., 2021), trading predictions (Ghorbani & Chong, 2020; Ingrassia et al., 2005), and FI (Gharbi & Kammoun, 2023; Nguyen, 2021; Nizam et al., 2020; Ahamed & Mallick, 2019; Camara & Tusta, 2017). This study builds on these advancements by leveraging PCA to construct a multidimensional FI index for Ethiopia, integrating bank-level data across traditional and digital financial dimensions. By addressing the challenges of dimensionality and ensuring robust variance capture, PCA offers a methodologically sound approach to analyze FI trends and inform policymaking in Ethiopia.

3. Methods and Materials

3.1 Data Source and Type of Data

Based on the data compiled from National Bank of Ethiopia financial stability report (NBE-FSR) (2024), commercial banks hold for 91.2% of total assets, 97.8% of deposits, 93.9% of credit, and 76.1% of equity in the financial sector, as of June 30, 2023. In light of this dominance, the researchers deal with data on commercial banks, which is explained by the fact that commercial banking institutions are the most dominant and basic point of access to the most basic forms of financial services. Due to data availability concern the researchers focus on 17 commercial banks. The study used secondary data. Data for the study sourced from various reliable institutions, like NBE, Commercial banks (CBs) annual report, and World Bank (WB). Table 1 summarizes the measurement variables and data sources for both the traditional and digital indices covering the period 2015-2023.

3.2 Index measurement

The process of constructing an index involves careful steps such as selecting indicators, normalizing data, assigning weights, and aggregating the final results (OECD, 2008). This study starts index development process through selecting critical indicators. Secondly, normalization ensures all indicators are on a comparable scale. Thirdly, weights are assigned to each indicator and dimension, reflecting their relative importance. Finally, researchers aggregate these weighted dimensions into a single FI, providing a composite FI measure of the phenomenon under study.

3.2.1 Identification of indicators

Recognizing the pioneering work of Beck et al. (2007), Sarma (2008), and Sarma & Pais (2011) in developing FI indices, this study employs indicators across three key dimensions: availability (outreach), access (penetration), and usage.

Table 1: Overview of indicators and data sources used in the study

Dimensions	Indicators	Abbreviations	Sources
Traditional Availability	Commercial bank branches (per 100,000 adults)	BrP	NBE; WB
	Commercial bank branches (per 1000km^2)	BrA	NBE; WB
	Automated teller machines (ATMs) (per 100,000 adults)	AtP	NBE; WB
	Number of ATMs (per 1000km^2)	AtA	NBE; WB
	Number of PoSs (per 100,000 adults)	PoP	NBE; WB
	Number of PoSs (per 1000km^2)	PoA	NBE; WB
Digital Availability	Number of agents (per 1,000 adults)	AP	NBE; WB
	Number of agents (per 1,000km^2)	AA	NBE; WB
Digital Accessibility	No of mobile active users (per 1,000 adults)	MBP	NBE; WB
	No of internet active users (per 1,000 adults)	IBP	NBE; WB
	No of mobile money (wallet) users (per 1,000 adults)	WP	NBE; WB
Traditional Usage	Depositors with commercial banks (per 1,000 adults)	DCP	CBE; WB
	Number of debit cards per 1,000 adults.	AcP	NBE; WB
	Outstanding loans and advances (% of GDP)	LGDP	NBE
	Outstanding deposits (% of GDP)	DGDP	NBE

Source: Prepared by authors

A. Availability

This dimension measures the unimpeded utilization of basic banking services for all customers. It reflects the infrastructure preparedness of the bank to ensure reachability (Hanivan & Nasrudin, 2019). The availability dimension of FI is typically assessed through geographic or demographic penetration metrics (Beck et al., 2007). Beck et al. (2007) operationalized this dimension by using indicators such as the density of ATMs and commercial bank branches. These indicators were scaled based on demographic factors (number of ATMs and branches per 100,000 adults) and geographic factors (number of ATMs and branches per 1,000 square kilometers). Consequently, for measuring this dimension, researchers analyze data on the number of branches, ATMs, and point-of-sale (PoS) machines, considering both the demographic density (per 100,000 adult people) and geographic distribution (per 1,000 km²). In addition, Tram et al. (2023) and Nguyen (2021) used mobile money agents to measure digital availability dimension. This study uses agent banking per 1000 adult population (demographic spread) and per 1000km² (geographic spread) as a proxy to measure digital availability dimensions. This approach aims to offer financial services in areas lacking bank branches and ATM facilities.

B. Accessibility

The accessibility aspect of FI goes beyond just the presence of financial institutions. It focuses on how easily individuals can make use of the services provided, with a primary focus on the ability to access financial services and products from formal institutions (Mushtaq and Shah, 2018). Therefore, utilizing digital channels to enhance the accessibility of financial services emerges as a highly accessible tool for FI (Lenka & Barik, 2018). Nguyen (2021) and Ismael & Ali (2021) used the number of mobile money accounts per 1,000 people to measure the accessibility aspect. Additionally, Ismael & Ali (2021) used internet banking service users as a proxy to measure this dimension. As a result, this study employs mobile banking, internet banking, and mobile money (wallet) accounts per 1,000 adult populations as a proxy to measure digital accessibility dimension.

C. Usage

Usage focuses more on the permanence and depth of financial services and/or products use. It requires detailed analysis of the regularity, frequency, and duration of usage over time, as well as the specific combination of financial products adopted by individuals or households (Mushtaq and Shah, 2018). As Kempson et al. (2004) aptly demonstrate, mere access may be insufficient due to factors like service quality or geographic remoteness, active utilization is essential. To measure the extent of usage, Ahamed & Mallick (2019) and Camara & Tusta (2017) utilized the indicator of deposit bank accounts, while Ismael & Ali (2021) focus on the number of debit cards per 1,000 adults. To capture the financial depth, which reflects the level of financial institution involvement within an economy, scholars have employed alternative metrics. As a proxy, Sarma (2016), Sarma & Pais (2011), and Nguyen (2021) all adopted the volume of credit and deposits relative to GDP. Specifically, outstanding deposits as a percentage of GDP and outstanding loans and advances as a percentage of GDP have been established as metrics to measure this dimension. To that end, this study uses deposit accounts and debit cards per 1,000 adult populations, along with the loan/GDP and deposit/GDP ratio, as indicators to measure the usage aspects of traditional FI dimension.

3.2.2 Normalization of selected variables

Normalization is crucial for comparing indicators with different measurement units and ranges. Various normalization methods include ranking, standardization (z-score), min-max (rescaled index), and logarithmic transformation (Carrino, 2015; Freudenberg, 2003; OECD, 2008). For this study, the min-max approach is used to normalize the indicators to values between 0 and 1, where the minimum value 0 indicates financial exclusion and the maximum value 1 indicates financial inclusion. To put all indicators on the same comparable scale, this study uses the following formula.

$$\text{Min} - \text{Max Approach} = \frac{\text{Actual Value} - \text{Minimum Value}}{\text{Maximum Value} - \text{Minimum Value}}$$

3.2.3 Indicator weighting

Indicator weighting is the most sensitive step in index construction (Papathoma-Kohle et al., 2019; Lockwood, 2004). Data-driven weights allow the data to determine the weights using statistical methods like PCA. PCA offers a data-driven technique, ensuring the index accurately reflects the underlying FI phenomena (Camara & Tuesta, 2017). It effectively reduces data dimensionality while preserving much information (Hair et al., 2019). Unlike pre-specified methods, PCA avoids subjective decisions on common factor structure, enhancing objectivity and robustness (Steiger, 1979; Jolliffe & Cadima, 2016), where the optimal number of common factors may not be evident or may vary across time and space. Additionally, PCA endogenously determines component weights, capturing the inherent variability within the data (Hanivan & Nasrudin, 2019). To that end, this study uses PCA, a data-driven approach, to assign weights and construct the financial inclusion index (FII).

3.2.4 Financial inclusion index aggregation and development

Disaggregating the overall index into sub-indices for traditional and digital inclusion provides policymakers with granular insights in directing their efforts to the areas that need improvement. While single-level multivariate analysis offers dimensionality reduction, it can struggle with nested data structures (Yang et al., 2022). This limitation arises from the assumption of independent and identically distributed (iid) data, potentially overlooking valuable information specific to different groups. To address this challenge, a multi-stage multivariate approach is employed. This approach acknowledges the hierarchical structure of the data, leading to a more precise analysis (Yang et al., 2022; Hox, 2013). As well, single-stage statistical approach PCA can be biased towards the weights of individual indicators. However, employing a multilevel (stage-based) parametric approach helps mitigate this issue. This strategy is preferred because each sub-index is defined by a set of correlated indicators, making it more advantageous to estimate the sub-indices first rather than estimating the overall index in one stage with all the indicators at one time (Ismael & Ali, 2021; Camara & Tuesta, 2017; Nagar & Basu, 2002).

3.2.4.1 The first stage PCA

This intra-group (first stage) stage focuses on using individual indicators within each dimension of FI to create sub-indices. This stage allows including correlated indicators within each dimension to capture the underlying structure effectively. PCA helps reduce redundancy and identify the most important factors explaining the variance within that dimension. So, the researchers classified 10 indicators for traditional sub-indices (6 indicators for availability and 4 indicators for usage) and 5 indicators for digital approach (2 indicators for availability and 3 for accessibility). For each index, the three unobserved endogenous variables (Y_i^a, Y_i^p, Y_i^u) are estimated along with their corresponding parameters (γ, δ) for TFI and (ρ, θ) for DFI using the equation as:

I. The dimensions of "availability," and "usage" of the traditional FI index are computed by the following equation system:

$$Y_i^a = \gamma_1 BrP_i + \gamma_2 BrA_i + \gamma_3 AtP_i + \gamma_4 AtA_i + \gamma_5 PoP_i + \gamma_6 PoA_i + \upsilon_i \tag{1}$$

$$Y_i^u = \delta_1 DCP_i + \delta_2 AcP_i + \delta_3 DGDP_i + \delta_4 LGDP_i + \varepsilon_i \tag{2}$$

II. The dimensions of "availability", and "penetration" of the digital FI index are computed by the following equation system:

$$Y_i^a = \rho_1 AP_i + \rho_2 AA_i + €_i \tag{3}$$

$$Y_i^p = \theta_1 MBP_i + \theta_2 IBP_i + \theta_3 WP_i + €_i \tag{4}$$

Each indicators weight will be extracted based on eq (1, 2, 3, 4).

3.2.4.2 The second stage PCA

In the second stage, the researchers apply the same procedure as in the first stage to perform inter-group analysis. This involves computing the cumulative weights for overall FI, integrating both traditional and digital financial dimensions. The study follows such approaches as:

$$\mathrm{FII}_T = \omega_1 Y^a + \omega_2 Y^p + \omega_3 Y^u + \varpi_1 Y^a + \varpi_2 Y^p + e_1 \tag{5}$$

Where $\mathrm{FII_i}$ is the overall FI index for each bank; ω_i, represents weights of traditional FI and ϖ_1 represents weights of accessibility digital FI, e_1 is variation due to error. These weights represent the significance of each dimension in the overall FI index. Consequently, higher weights indicate greater importance of a dimension, suggesting that policymakers should focus more on this dimension to effectively enhance FI.

4. Result and Discussion

4.1 Descriptive Analysis

The descriptive statistics in Table 2 summarizes the basic characteristics of the variables used to construct the TFI and DFI sub-indices of overall FI index. There are 153 sample sizes (taking 8 years for 17 commercial banks) used to develop FI index. It provides information on the mean, mean squared error (MSE), minimum, and maximum values for each variable.

Table 2: Summary descriptive statistics

Dimensions	Variable	Obs	Mean	MSE	Min	Max
Availability TFI	*BrP*	153	0.4840	0. 0337	0.0054	2.6737
	BrA	153	0.2827	0. 0276	0.0027	1.7261
	AtP	153	0.4039	0. 0226	0	5.9626
	AtA	153	0.2383	0. 0233	0	3.5018
	PoP	153	0.8161	0. 0309	0	11.6824
	PoA	153	0.4699	0. 0323	0	6.4249
Usage TFI	*DCP*	153	13.1927	0. 0151	0	361.0142
	AcP	153	42.3526	0. 0245	0.2991	553.2191
	LGDP	153	0.0093	0.0344	0.0003	0.0876
	DGDP	153	0.0174	0. 0391	0.0006	0.2052
Availability DFI	*AP*	153	2.5187	0. 0106	0	100.5907
	AA	153	1.5621	0. 0103	0	64.9387
Accessibility DFI	*MBP*	153	7.5166	0. 0161	0	130.7813
	IBP	153	1.4200	0. 0103	0	53.7799
	WP	153	7.7405	0. 0159	0	191.9803

Source: Computed based on Stata 14 output

4.4.1 Pre-principal component analysis tests

The researchers used a max-min normalization method to address scale differences among the FI sub-indicators while constructing the FI index before applying PCA. PCA can be carried out by performing eigenvalue decomposition on a data covariance matrix or singular value decomposition on a data matrix, usually after normalization of the data matrix for each attribute (Osawaru et al., 2015).

4.4.1.1 Adequacy tests

Table 3: KMO Measure & Bartlett's Test of Sphericity for traditional & digital datasets

Dimensions	Abbreviations	KMO	Overall KMO	Bartlett's test of sphericity
Traditional Availability	BrP	0.6974	0.69430	*P*-value = 0.000 Chi-square = 3347.798(15*)
	BrA	0.6875		
	AtP	0.6929		
	AtA	0.6851		
	PoP	0.6931		
	PoA	0.7104		
Digital Availability	AP	0.5	0.5	*P*-value = 0.000 Chi-square = 1,119.314 (1*)
	AA	0.5		
Digital Accessibility	MBP	0.5370	0.5569	*P*-value = 0.000 Chi-square = 221.805 (3*)
	IBP	0.7997		
	WP	0.5332		
Traditional Usage	DCP	0.5593	0.6168	*P*-value = 0.000 Chi-square = 1,111.108 (6*)
	AcP	0.6725		
	LGDP	0.5795		
	DGDP	0.6540		

Source: Calculated based Stata result, parentheses indicate the degree of freedom

Before using PCA, certain preliminary tests must be conducted. Firstly, the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity should be performed. These tests ensure that the sample size is adequate and that the selected indicators are sufficiently intercorrelated (Ismael and Ali, 2021; Taherdoost et al., 2014). A KMO (Measure of sampling adequacy) value greater than or equal to 0.5 and a statistically significant chi-square statistic in Bartlett's (1950) test indicates suitability for factorization; otherwise, factorization is not recommended (Hair et al., 2019).

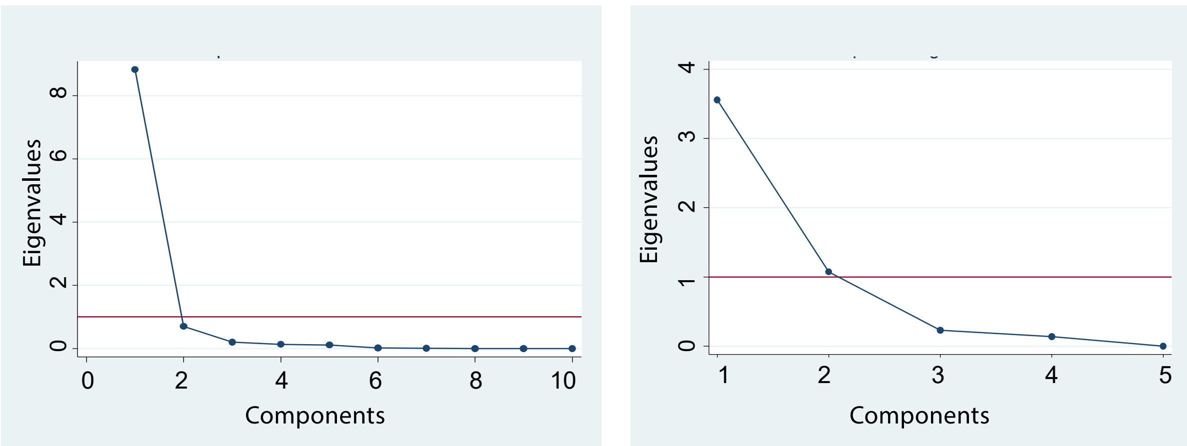
Additionally, the Kaiser criterion is often employed alongside a scree plot, where eigenvalues are plotted against the number of factors. This graphical method helps identify the optimal number of factors by observing the point where the plot's curve shows an elbow, indicating a less steep decline. Factors beyond this elbow point are typically excluded (Cleff, 2019).

The result mentioned on Table 3 and figure 1 reveals that all components meet KMO, sphericity test requirements (KMO ≥ 5, sphericity ≤ 0.05 and scree plot line separates from the ideal eigenvalue line i.e., 1) to use PCA for FI development.

Figure 1: Scree plot of both traditional (a) and digital financial (b) inclusion dimensions

(a) (b)

Scree plot for traditional FI dimensions   Scree plot for digital FI dimensions



Source: Stata scree plot result

Lastly, an evaluation of the index's internal consistency was carried out through a reliability test. Reliability pertains to the level of uniformity in measurement among comparable subjects in comparable circumstances (Ursachi et al., 2015). The examination of the reliability of the variables considered in this study is assessed using Cronbach's alpha coefficient (CA), as recommended by Hair et al. (2019). According to Kline (2015), a CA value greater than 0.6 is deemed acceptable for scales under development. The obtained value of 0.9721 in the above (Table A3), surpassing the suggested threshold of 0.6, demonstrates outstanding internal consistency and bolsters the trustworthiness of our data.

4.4.2 Principal component analysis

4.4.2.1 First stage principal component analysis

Following the verification of data adequacy, a two-stage PCA was employed to ex-tract latent variables representing key dimensions of FI. In the first stage, as shown in Table 4, intra-group eigenvalues were calculated for both traditional (availability and usage) and digital (availability and accessibility) dimensions within each sub-index. According to Kaiser's criterion (1960), eigenvalues greater than 1 indicate components that capture a significant portion of the variance.

This study founding identified that only the first principal component (PC1) for each dimension had an eigenvalue exceeding 1. Therefore, subsequent analysis focused exclusively on these first principal components. The weights associated with these components were utilized to estimate latent variables representing penetration (Yp), availability (Ya), and usage (Yu).

Table 4: Estimation of PC and eigenvalue of sub-indices of TFI and DFI

Component	Eigenvalue	Difference	Explained variance (EV)	Cumulative EV
Availability TFI				
Comp1	5.4682	5.1268	0.9114	0.9114
Comp2	0.3415	0.1566	0.0569	0.9683
Comp3	0.1849	0.1801	0.0308	0.9991
Comp4	0.0048	0.0043	0.0008	0.9998
Comp5	0.0004	0.0002	0.0001	0.9999
Comp6	0.0003		0.0000	1
Availability DFI				
Comp1	1.9997	1.9994	0.9999	0.9999
Comp2	0.0003		0.0001	1
Accessibility DFI				
Comp1	2.0686	1.2765	0.6895	0.6895
Comp2	0.7921	0.6528	0.2640	0.9536
Comp3	0.1373		0.0464	1
Usage DFI				
Comp1	3.4725	2.9920	0.8681	0.8681
Comp2	0.4804	0.4430	0.1201	0.9882
Comp3	0.0374	0.0278	0.0094	0.9976
Comp4	0.0096		0.0024	1

Source: Computed based Stata 14 result

Hair et al. (2019) considered acceptable solutions with an explained variance (EV) of 60% or higher. It is noteworthy that the traditional availability and usage dimensions, as represented by PC1, account for a significant portion of the variance (91.1% and 86.8%, respectively), indicating a strong explained information they capture (Table 4). This aligns with the expectation that indicators in both availability and usage dimension contribute to FI index development.

For the digital inclusion dimensions, PC1 explains a near-perfect 99.9% of availability-related information, highlighting its dominance. However, for accessibility, PC1 explains a more moderate 69% of the variance. This suggests that indicators under digital availability and accessibility contribute a significant role in financial index development.

Table 5: Scoring coefficients for orthogonal varimax rotation (weights)

Dimensions	Indicators	Comp1	Unexplained	Normalized weights
Traditional Availability	BrP	0.4146	0.0600	0.16927
	BrA	0.4105	0.0786	0.16759
	AtP	0.4112	0.0753	0.16790
	AtA	0.4078	0.0908	0.16649
	PoP	0.3983	0.1324	0.16263
	PoA	0.4069	0.0948	0.16612
Digital Availability	AP	0.7071	0.0001	0.5
	AA	0.7071	0.0001	0.5
Digital Accessibility	MBP	0.6382	0.1574	0.375736
	IBP	0.4067	0.6578	0.239446
	WP	0.6536	0.1162	0.384818
Traditional Usage	DCP	0.4691	0.2360	0.234706
	AcP	0.5195	0.0627	0.259963
	LGDP	0.4978	0.1396	0.249065
	DGDP	0.5121	0.0892	0.256266

Source: Computed based Stata 14 result

The normalized weights derived from the intra-group PCA are shown in Table 5. These weights indicate the significance of each indicator in elucidating the variance associated with each principal component 1.

With regard to the traditional availability dimension, the weights assigned to the first component are as follows: 0.1693 (BrP); 0.1676 (BrA); 0.1679 (AtP); 0.1665 (AtA); 0.1626 (PoP); 0.1661 (PoA). The study revealed that branch availability has the highest relative weight compared to ATMs and PoS machines in both demographic and geographic analyses. This indicates that branch expansion plays a crucial role in overall availability in the Ethiopian context, surpassing the importance of alternative channels such as ATMs and PoS. This dominance aligns with contextual realities such as high adult illiteracy rates (48.2%) (Abate & Adamu, 2022) that necessitate in-person banking services. Furthermore, the ad hoc policy measures such as (NBE directive-SBB/66/2018) mandating the preservation and expansion of branch network, have led to an increase of over 137% in the total number of bank branches, rising from 4,757 in 2018 to 11,281 in 2023. Supporting the findings of Alemu (2014), CSA et al., (2021) and Mossie (2022), the lack of physical access to banking services is a main factor contributing to the exclusion of the most vulnerable segments of society. These initiatives underscore the critical need to maintain and expand branch networks, reflecting reactive policy strategies aimed at improving access to financial services, particularly in underserved regions. Consequently, transaction volumes processed through branches (Birr 10.3 trillion) significantly outpace those through ATMs and PoS (Birr 519.1 billion) (NBE-FSR, 2024), emphasizing the importance of branch-based banking in developing economies. While such initiatives support availability, they also entail high operational costs. Therefore, complementary measures like financial literacy programs are crucial to transition users toward digital platforms. Evidence from Mishra et al. (2024) suggests that targeted literacy campaigns can significantly enhance FI in contexts with low formal education levels.

In addition, the intra-group analysis reveals that deposit accounts (0.26) hold the highest weight within the traditional usage dimension, followed by the DGDP ratio (0.2563). This trend aligns with targeted initiatives and supports the findings of Fielding & Regasa (2024), highlighting the increasing competition in the banking sector. Specifically, it underscores the Ethiopian banking industry's focus on deposit mobilization, which has been intensified by heightened competition. The number of commercial banks nearly doubled from 17 in 2015 to 31 in 2023, resulting in a 500% growth in total deposits (24.8% of GDP) by 2023 (NBE-FSR, 2024). Based on the second NFIS strategic plan (NFIS, 2021), the government has set an objective to enhance and expand FI, aiming for 70% of adults to possess a bank account by 2025. In pursuit of this goal and to attract more deposits, banks employed aggressive customer acquisition strategies, while government initiatives such as (NBE directive- FXD/49/2017 & FXD/81/2022) have also encouraged deposit retention by restricting cash withdrawals. However, the lower weights of the LGDP ratio (0.2491) and debit card penetration (0.2347) point to challenges in achieving balanced geographical and demographic inclusion. The NBE-FSR (2024) highlights that 99.8% of loans are disbursed in urban areas, with the top ten borrowers accounting for 23.5% of total outstanding loans. This urban-centric and cream-screaming lending pattern underscores the need for broader outreach strategies to ensure equitable financial access. This observation is consistent with the findings of Kappeler et al. (2018), who noted that 70% of micro-firms and 40% of SMEs in Ethiopia encounter difficulties in securing credit.

With regards to digital availability dimension, both agency banking indicators (disaggregated demographically and geographically) receive equal weights (0.5), indicating their shared prominence. The rapid growth of Ethiopia's agent network, which expanded from three agents per 100,000 adults in 2016 to 77 per 100,000 by 2020 (NFIS, 2021), reflects the government's targeted intervention to enhance FI. Ethiopia's agent banking model, introduced under directive (NBE directive-FIS/02/2020) has provided a regulatory framework to facilitate this growth. Although still in its nascent stages, the adoption of scalable and efficient agent banking models is critical for overcoming infrastructural constraints and fostering value creation through innovative financial services (Mishra et al., 2024; Diniz et al., 2012).

Geographical disparities in FI remain significant, particularly in rural areas where limited infrastructure restricts access to financial services (Beck et al., 2007). Technological innovations. such as mobile and internet banking, are beginning to address this urban-rural divide, as documented in studies of mobile money adoption across Africa (Mishra et al., 2024). To that end, within digital accessibility dimension, WP holds the highest weight (0.3848), followed by MBP (0.3757) and IBP (0.2394). This suggests that mobile money wallets are the most preferred mode of digital financial access for the mass population. This aligns with the ease of opening mobile money accounts using just a phone number, in contrast to the more intricate processes involved in mobile and internet banking. Consequently, mobile wallets have become the preferred mode of digital financial access, facilitating transactions such as bill payments, mobile data charges, and peer-to-peer transfers. In contrast, internet banking's lower weight suggests it primarily caters to high-net-worth clients, reflecting a deliberate targeting strategy by Ethiopian banks. This finding aligns with observations by Mishra et al. (2024), who noted similar patterns in other developing economies where internet banking remains a premium service. Meanwhile, mobile banking adoption has been bolstered by cash limit directives (Directive Nos. FXD/49/2017 and FXD/81/2022), which incentivize digital transactions due to their enhanced security features compared to mobile wallets. The prevailing market position of mobile payment services signals a broader shift toward the dematerialization of payment methods, a trend with significant implications for advancing FI in Ethiopia.

4.4.2.2 Second stage principal component analysis

Building upon the first-stage analysis, the study employed the second stage-PCA to establish the weights of the four dimensions in developing the overall FI index. Similar to the first stage, adequacy tests were conducted to ensure the suitability of PCA for this analysis. As presented in Table A2 & Figure B1, the KMO measure (0.6361) satisfies KMO > 0.5 (Hair et al., 2019), Bartlett's (1950) test of sphericity (p-value < 0.0001), and the scree plot (Cattell, 1966) all satisfied the criteria for applying PCA.

It's important to clarify that the second-stage analysis focuses on inter-group rather than intra-group comparisons. This approach aims to identify group-specific drivers of FI. While intra-group PCA provides insights into the internal structure of the FI index within each group, inter-group PCA addresses how these dimensions differentiate FI levels across groups.

The extraction of a dominant principal component (PC1), based on eigenvalues presented in Table 6 (3.20, 0.53, 0.25, and 0.02), captures the most significant variation in the data across groups. Following the criterion (eigenvalue > 1), only PC1 is retained for further analysis. The weights assigned to each dimension within PC1 are critical indicators of their influence on the overall FI index in a group-specific context. This PC1 determines the weights assigned to each of the four dimensions in the overall FI index development, ensuring a comprehensive understanding of FI dynamics across different groups.

Table 6: Overall principal component analysis

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.20293	2.67426	0.8007	0.8007
Comp2	0.528673	0.281266	0.1322	0.9329
Comp3	0.247407	0.226421	0.0619	0.9948
Comp4	0.0209866		0.0052	1

Source: Computed based Stata 14 result

Concerning the principal components' structure, in Table 6, it is noted that the first component, responsible for 80.07% of the total data variation, indicates that only 19.97% of the variation is not accounted for; hence, it is considered a satisfactory extraction based on Hair et al. (2019). This result helps in reducing the number of selected components, as out of four components, one component has an eigenvalue exceeding 1, which the researchers retain to establish the FI index.

Table 7: Scoring coefficients (weights) using orthogonal varimax rotation

Indicators	Comp1	Unexplained	Normalized weights
tAvailability	0.5240	0.1205	0.2625
tUsage	0.5223	0.1263	0.2616
dAvailability	0.4500	0.3515	0.2254
dAccessibility	0.5002	0.1987	0.2505

Source: Computed based Stata 14 result

Based on the findings presented in Table 7, Equation (6) constructs the composite FI index (FII), emphasizing different dimensions' contributions:

$$\text{FII} = 0.2625Y_i^{at} + 0.2616Y_i^{ut} + 0.2254Y_i^{a_d} + 0.2505Y_i^{p_d} + e_i \quad (6)$$

Where,

FII, represents overall FI index.

$Y_i^{a_t}$, denotes traditional availability dimension.

$Y_i^{u_t}$, denotes traditional usage dimension.

$Y_i^{a_d}$, represents digital availability dimension.

$Y_i^{p_d}$, represents penetration (accessibility) dimension.

The equation reveals that traditional availability (0.2625) has the highest normalized weight, indicating that expanding financial institution infrastructure significantly impacts the overall FII. This finding aligns with existing literature (e.g., Nguyen, 2021; Gharbi & Kammoun, 2023) and the researchers' expectations, emphasizing the importance of infrastructure development alongside financial literacy and user adoption. Usage (0.2616) is the second most significant dimension for overall FI, highlighting the importance of account usage and engagement with formal financial services. Digital accessibility (0.2505) ranks third, reflecting the growing role of digital tools in FI. However, agency banking has the lowest weight (0.2254), suggesting that while digital tools are cost-effective, targeted efforts are needed to reach vulnerable populations, such as women, rural residents, and those with low literacy.

4.4.3 Measuring commercial banks' contribution for financial inclusiveness

Table 8 details the estimation of dimensions of the FI index. Notably, on average, the national FI score exhibits a substantial increase, rising from 10.89% in 2015 to 52.18% in 2023. This upward trajectory aligns with the launch of Ethiopia's National FI Strategy in 2015, which demonstrably facilitated broader entry to the formal financial sector. Historically, financial exclusion in Ethiopia has been both voluntary and involuntary (Desalegn & Yemataw, 2017). However, the observed improvement in FI score reflects a combination of technological advancements, socio-economic progress, and targeted government interventions.

A. Role of technological innovations

The adoption of core banking systems, particularly Temenos' T24 platform since 2012 by the Commercial Bank of Ethiopia (CBE), has been instrumental in expanding access. Innovations like Temenos' Arc Mobile have enabled banks to deliver advanced mobile banking services, such as SMS alerts, interactive SMS capabilities, and web-based financial services, thereby addressing the needs of previously unbanked populations. As more banks digitalized their operations, FI scores steadily improved across all dimensions, underscoring the transformative impact of digital technology.

B. Impact of government policies

Government-led initiatives have been instrumental in advancing FI through targeted policies. One notable measure was the introduction of interest-free banking within the conventional banking framework in 2011, which was later expanded by the Banking Business Proclamation Amendment (No. 1159/2019) to permit fully-fledged interest-free banks (Ahmed, 2020). This initiative widened the scope of formal financial services, particularly among communities with preferences for Sharia-compliant banking. Additionally, the licensing of Safaricom Ethiopia under the National Digital Payment Strategy (NDPS) marked a significant milestone in strengthening

Ethiopia's telecom infrastructure. The subsequent introduction of mobile payment platforms, such as TeleBirr by Ethio-telecom in 2021, further propelled digital accessibility. By June 2023, TeleBirr had amassed over 36 million users, facilitating transactions worth Birr 856.22 billion (approximately USD 15 billion) and integrating with 23 banks. Consequently, the banking sector made substantial investments in digital technologies, particularly in mobile wallets. This expansion is reflected in the digital accessibility FI score, which increased from 0.09 in 2019 to 0.57 in 2023, reflecting an increase of over 533% (see Table 8). These findings underscore the effectiveness of policy reforms in enhancing DFI.

Table 8: Estimation of FI dimensions

	tAvailability	tUsage	dAvailability	dAccessibility	Mean
2015	0.2014	0.2257	0.0013	0.0071	0.1089
2016	0.2980	0.2476	0.0078	0.0170	0.1426
2017	0.3639	0.2812	0.0158	0.0304	0.1728
2018	0.4038	0.3061	0.0326	0.0448	0.1968
2019	0.4638	0.3355	0.0423	0.0899	0.2329
2020	0.5320	0.3540	0.0734	0.1925	0.2880
2021	0.5541	0.4074	0.0507	0.2859	0.3245
2022	0.6364	0.4178	0.2574	0.4253	0.4342
2023	0.7152	0.4346	0.3654	0.5720	0.5218

Source: Computed based Stata 14 result

C. Enabling infrastructure for financial inclusion

Infrastructure initiatives have further addressed critical barriers to FI. The National Electrification Program (2017) aims for universal electricity access by 2025, providing 65% of households with grid connections and 35% with off-grid solutions (Gebremeskel et al., 2021). Electricity availability is foundational for the growth of digital financial services, including Pay-As-You-Go (PAYGo) solar solutions, which also facilitate micro-credit access. Concurrently, the government's Digital Ethiopia strategy has introduced revised digital payment directives (ONPS/01/2020 and ONPS/09/2023), enabling a regulatory framework for fintech companies. These structural changes create an ecosystem conducive to FI.

The Fayda Digital ID initiative, launched in 2021, is another transformative development. This biometric ID system is designed to enhance Know Your Customer (KYC) compliance and reduce identity fraud, enabling banks to expand services to unbanked populations. Once fully operationalized, this initiative is expected to significantly enhance FI by addressing accessibility barriers.

D. Socio-economic dynamics and autonomous developments

Socio-economic and technological advancements have also played a crucial role in shaping Ethiopia's FI landscape. The COVID-19 pandemic acted as a catalyst, accelerating the adoption of digital financial services as physical interactions became restricted and prompted increased reliance on mobile and internet banking. This shift was facilitated by substantial growth in mobile and internet subscribers. Based on Ethio-telecom annual performance report for (2023), between 2019 and 2023, mobile subscribers increased by 66%, rising from 41.9 million to 69.5 million, while data and internet subscribers grew by 40%, from 22.3 million to 31.3 million. Consequently, the average FI score rose from 23.3% in 2019 to 52.18% in 2023, representing a 124% increase. This upward trend underscores the synergistic effects of autonomous developments, such as the expansion of mobile networks, alongside ad hoc measures like regulatory reforms.

The analysis of banking institution rankings by FI index in (Table A4) reveals a pronounced disparity in FI across bank sizes. Notably, the Commercial Bank of Ethiopia (CBE), the only large-sized bank in Ethiopia as revealed by NBE, on average contributes a substantial 48.99% to the overall national FI score. Conversely, as detailed in (Table A1), five medium-sized commercial banks collectively contribute 29.26%, while the contribution of eleven small-sized banks is even lower at 21.75%.

Table 9: FI Score of Ethiopian commercial banks

CBEs\Year	2015	2016	2017	2018	2019	2020	2021	2022	2023	Average Share	Rank
CBE	0.2438	0.3332	0.3764	0.4047	0.4578	0.5641	0.5423	0.7380	0.7989	0.4955	1
Dashen	0.0394	0.0432	0.0475	0.0561	0.0830	0.1005	0.1148	0.1559	0.2226	0.0959	2
Awash	0.0288	0.0355	0.0455	0.0544	0.0642	0.0782	0.1259	0.1792	0.2222	0.0926	3
Abyssinia	0.0155	0.0211	0.0289	0.0346	0.0414	0.0596	0.0972	0.1703	0.2052	0.0749	4
CBO	0.0139	0.0173	0.0333	0.0448	0.0535	0.0715	0.0864	0.1180	0.1703	0.0677	5
Wogagen	0.0172	0.0209	0.0276	0.0334	0.0405	0.0514	0.0599	0.0658	0.0736	0.0434	6
United	0.0171	0.0185	0.0245	0.0288	0.0339	0.0393	0.0436	0.0484	0.0543	0.0343	7
Nib	0.0138	0.0157	0.0215	0.0261	0.0310	0.0348	0.0411	0.0428	0.0514	0.0309	8
OIB	0.0128	0.0160	0.0185	0.0224	0.0273	0.0289	0.0340	0.0420	0.0630	0.0294	9
Lion	0.0079	0.0125	0.0176	0.0218	0.0260	0.0361	0.0404	0.0404	0.0403	0.0270	10
Abay	0.0070	0.0101	0.0124	0.0150	0.0180	0.0211	0.0276	0.0373	0.0497	0.0220	11
Bunna	0.0061	0.0079	0.0110	0.0137	0.0156	0.0195	0.0268	0.0289	0.0517	0.0201	12
Birhan	0.0054	0.0086	0.0133	0.0150	0.0186	0.0214	0.0257	0.0310	0.0360	0.0194	13
Zemen	0.0028	0.0042	0.0048	0.0057	0.0075	0.0087	0.0110	0.0139	0.0181	0.0085	14
Addis	0.0018	0.0027	0.0039	0.0046	0.0052	0.0060	0.0069	0.0080	0.0088	0.0053	15
Debub	0.0010	0.0014	0.0020	0.0026	0.0036	0.0058	0.0080	0.0090	0.0106	0.0049	16
Enat	0.0011	0.0018	0.0025	0.0037	0.0043	0.0049	0.0066	0.0079	0.0104	0.0048	17

Source: Computed based on Stata 14 result

This observed pattern aligns with the researchers' expectation, suggesting that large banks currently offer more inclusive financial services and possess a more extensive infrastructure compared to their medium and small-sized counterparts. This finding underscores the potential presence of inclusion gaps among small and medium-sized commercial banks in Ethiopia. To address this disparity and promote shared prosperity, the implementation of tailored FI initiatives as a national strategy appears highly recommended.

4.4.4 Verifying the strength of the FI index

Building on the work of Ahamed & Mallick (2019), Nguyen (2021), and Gharbi & Kammoun (2023), the researchers perform a robustness test to assess the validity and stability of the newly developed FI index compared to existing FI indices. This involves conducting a validity test to confirm the reliability of the new FI index.

The researchers used deposit and real lending interest rates (RLIR) as essential variables to validate the developed FI index from Ethiopian context. Deposits are vital for banks, as they are the primary source of working capital and crucial for bank sustainability and profitability (Nesru & Mekonnen, 2022; Namazi & Salehi, 2010). They also play a significant role in economic growth by increasing investment (Tun, 2019; Gunasekara & Kumari, 2018) and enabling banks to extend credit, which is their main revenue stream (Viswanadham et al., 2013). Additionally, understanding RLIR helps individuals and businesses make informed financial decisions and strengthen banks' monitoring mechanisms (Moyo & Phiri, 2024).

To that end, the researchers used the overall average of FI of the country and measured the correlation between the saving and real lending interest rate and newly developed FI index. The Pearson correlation results presented in Table 10 show p-values of 0.0000 and 0.0002, respectively, indicating that the correlations are statistically significant at the 1% level (0.9617 for saving) and (0.9391 for real lending interest rate). These results therefore demonstrate the highly robustness of the newly created index.

Table 10: Pearson correlation between FI index, saving and real deposit interest rate

		FII
FII	Pearson Correlation	1
Saving	Pearson Correlation Sig. (bilateral)	0.9617*** 0.0000
RLIR	Pearson Correlation Sig. (bilateral)	−0.9391*** 0.0002

Source: Computed based on Stata 14 result

The results reveal a remarkably strong positive association between FI and savings (correlation coefficient = 0.96), and a strong negative association between FI and real lending interest rates (correlation coefficient = -0.93). Notably, these associations are significantly stronger than those reported by Gharbi & Kammoun (2023) (0.62 for FI and savings, -0.13 for FI and real interest rate). Moreover, this study result demonstrates statistically significant correlations at the 0.1% level for both variables.

The direction of the correlations aligns with theoretical expectations. Real lending interest rates are negatively correlated with FI, as high rates make loans more expensive and discourage access, particularly for low-income populations (Uddin et al., 2017). Conversely, in relation to deposits, a positive higher FI scores are associated with in-creased savings, likely due to a greater number of households having access to financial institutions and associated saving products (Gharbi & Kammoun, 2023). These robust correlations provide strong evidence for the construct validity of the newly developed FI index.

5. Conclusion and Recommendation

Recognizing the critical importance of FI, Ethiopia has extended its commitment with the second NFIS in 2021, building upon the initial strategy from 2015 to 2021. This study addresses a significant gap by developing a composite multidimensional index to measure FI in Ethiopia, using annual commercial bank data spanning from 2015 to 2023. The methodology employed a two-stage PCA approach, focusing on both traditional and digital indicators.

The result indicates that traditional dimensions of availability (0.2625) and usage (0.2616) are significant in determining the degree of the traditional financial index. In the digital aspect, digital accessibility (0.2254) encompassing tools like digital wallets, mobile banking, and internet banking, proves more determining than digital availability (0.2505), highlighting that the presence of banking institutions in remote areas remains limited. For enhanced FI, policymakers must address the needs of those involuntarily excluded from formal financial services. The evidence suggests that digitalization is a crucial strategy to engage these excluded groups. The findings also demonstrate that Ethiopia's efforts to improve financial inclusivity have markedly improved the country's FI score, rising from a low average of 10.9% in 2015 to a relatively high 52.2% in 2023. This study's FI index underscores that increasing both traditional and digital financial services is key to expanding the inclusiveness of the formal financial system.

The paper contributes significantly to the existing literature as the first comprehensive measurement of FI in Ethiopia, using both traditional and digital indicators. By evaluating the performance of commercial banks in providing financial services to underserved populations, it provides valuable insights for policy makers and financial institutions to make informed decisions and implement dimensionally tailored initiatives. Improving access to and building robust FI systems is crucial for integrating underserved and underbanked populations into the formal financial sector. Moreover, the incorporation of digital indicators, such as mobile money and agency banking in the calculation of the FI index represents a significant contribution of this study. This highlights the crucial role that digital tools play in enabling low-income individuals to access and use financial products and services.

Based on the study empirical results, the researchers provided the following government and commercial bank specific recommendations. First, the government should prioritize the expansion of the digital ecosystem and infrastructure while fostering an innovative-conducive environment to enhance FI. This will facilitate the implementation of the multidimensional FI measurement index, serving as a dynamic tool for monitoring progress, identifying gaps, and informing evidence-based policy decisions. Commercial banks, meanwhile, should prioritize expanding their reach in remote areas. Providing formal financial services through cost-effective approaches like agency banking and tailored digital solutions can increase accessibility and promote social inclusion.

For future studies may explore regional variations within Ethiopia, which might differ by the economic and social heterogeneity of the regions. Also, deeper insights require analysis of policy perspectives in the sector and inform tailored interventions to advance inclusive financial practices at regional and national levels.

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Author Contributions:

Mohammed Jatoro Arebo (Main author): conceptualization, methodology, formal analysis, investigation, data curation, software, writing - original draft, writing - review & editing.
Filmon Hadaro Hando (first contributor): resources, writing - review & editing
Andualem Goshu Mekonnen (second contributor): writing - review & editing
All authors have read and agreed to the published version of the manuscript.
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Appendix A

Table A1: List commercial banks in their type

Name of Commercial banks of Ethiopia	Short code	NBE-Category
Commercial Bank of Ethiopia	CBE	Large-sized
Awash International Bank	Awash	Medium-sized
Dashen Bank	Dashen	Medium-sized
Bank of Abyssinia	Abyssinia	Medium-sized
Wegagen Bank	Wogagen	Small-sized
United Bank	United	Medium-sized
Nib International Bank	Nib	Small-sized
Cooperative Bank of Oromia	CBO	Medium-sized
Lion International Bank	Lion	Small-sized
Buna International Bank	Bunna	Small-sized
Oromia International Bank	OIB	Small-sized
Zemen Bank	Zemen	Small-sized
Berhan International Bank	Berhan	Small-sized
Addis International Bank	Addis	Small-sized
Abay Bank	Abay	Small-sized
Debub Global Bank	Debub	Small-sized
Enat Bank	Enat	Small-sized

Source: Prepared by authors

Table A2: KMO Measure & Bartlett's Test of Sphericity for traditional & digital datasets

	Dimensions	KMO	Overall KMO	Bartlett's test of sphericity
Traditional Usage	tAvailability	0.5948	0.6361	P value = 0.000 Chi-square = 709.297(6*)
	tUsage	0.6121		
	dAvailability	0.6663		
	dAccessibility	0.6991		

Source: Computed based on Stata 14 result

Table A3: Data reliability test

Traditional indicators Scale reliability coefficient	0.9839
Digital indicators Scale reliability coefficient	0.8770
Overall FI indicators Scale reliability coefficient	0.9721

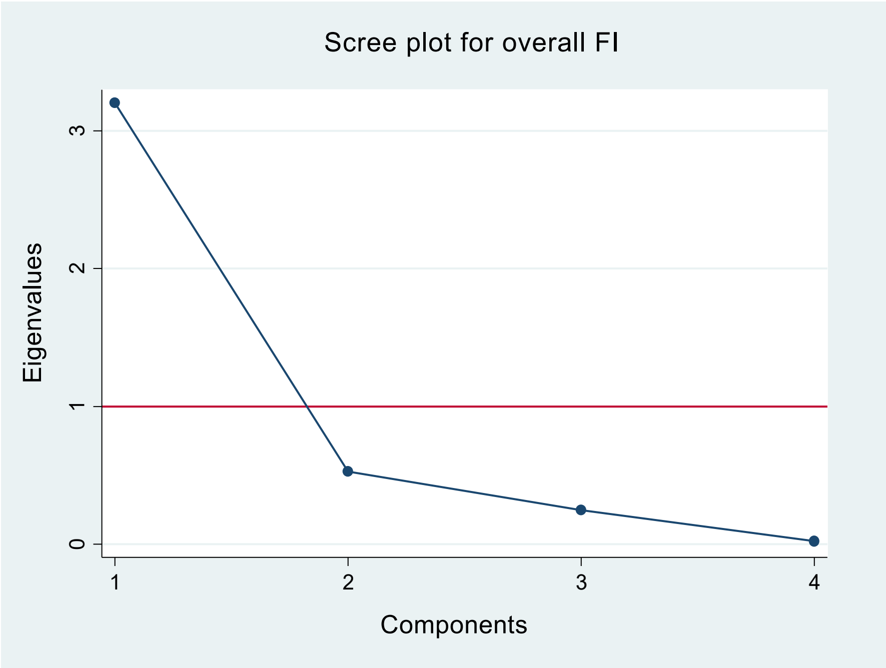
Source: Computed based on Stata 14 result

Table A4: Average contribution of each commercial bank from FI score

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023	Average score
CBE	0.5599	0.5840	0.5446	0.5140	0.4915	0.4897	0.4177	0.4249	0.3828	0.4899
Awash	0.0661	0.0622	0.0659	0.0691	0.0689	0.0679	0.0970	0.1031	0.1065	0.0785
Dashen	0.0905	0.0757	0.0687	0.0713	0.0891	0.0873	0.0884	0.0898	0.1067	0.0853
Abyssinia	0.0356	0.0370	0.0417	0.0440	0.0444	0.0518	0.0749	0.0981	0.0983	0.0584
Wogagen	0.0395	0.0367	0.0399	0.0424	0.0435	0.0446	0.0461	0.0379	0.0353	0.0406
United	0.0393	0.0325	0.0355	0.0365	0.0364	0.0341	0.0336	0.0279	0.0260	0.0335
Nib	0.0317	0.0275	0.0311	0.0331	0.0333	0.0302	0.0317	0.0247	0.0246	0.0298
CBO	0.0318	0.0302	0.0481	0.0569	0.0575	0.0621	0.0666	0.0680	0.0816	0.0559
Lion	0.0181	0.0218	0.0255	0.0276	0.0279	0.0313	0.0311	0.0232	0.0193	0.0251
Bunna	0.0141	0.0139	0.0158	0.0174	0.0167	0.0169	0.0206	0.0167	0.0248	0.0174
OIB	0.0293	0.0280	0.0267	0.0285	0.0293	0.0251	0.0262	0.0242	0.0302	0.0275
Zemen	0.0065	0.0074	0.0070	0.0073	0.0080	0.0076	0.0085	0.0080	0.0087	0.0077
Birhan	0.0124	0.0151	0.0192	0.0190	0.0200	0.0186	0.0198	0.0178	0.0172	0.0177
Addis	0.0042	0.0047	0.0056	0.0058	0.0056	0.0052	0.0054	0.0046	0.0042	0.0050
Abay	0.0161	0.0177	0.0180	0.0190	0.0193	0.0183	0.0212	0.0215	0.0238	0.0194
Debub	0.0024	0.0025	0.0029	0.0033	0.0038	0.0050	0.0062	0.0052	0.0051	0.0040
Enat	0.0025	0.0032	0.0037	0.0047	0.0047	0.0042	0.0051	0.0045	0.0050	0.0042

Source: Computed based on Stata 14 result

Figure B1: Scree plot for overall FI dimensions



Source: Computed based on Stata 14 result

Table A5: Overview of indicators and methods used in prior studies on FI measurement.

Author(s)	Methodology	Dimensions	Components
Ismail & Ali (2021)	Three stage PCA	Access (traditional FI dimension)	Number of ATM per 100,000 adult population
			Number of branches per 100,000 adult population
		Access (digital FI dimension)	Number of cellular mobile subscribers per 100 people
			Number of registered wallet (mobile money) accounts
			The percentage of internet users (mobile)
		Usage (traditional FI dimension)	Number of deposit accounts per 1,000 adult population
			Number borrowers per 1,000 adult population
			Number of debit cards per 1,000 adult population
			Number of credit cards per 1,000 adult population
		Usage (digital FI dimension)	Accounts for mobile payments
			Number of transactions per 1000 adults using mobile money
			Conduct online purchases or make online payment.
			Completed online purchase using mobile.
		Barriers (traditional FI dimension)	Number of branches per 1000km2
			Number of ATMs per 1000km2
			Obtained credit from financial institutions in rural areas
			Deposit made at financial institution in rural area (aged 15+)
Nguyen (2021)	Two stage PCA	Availability	Number of branches per 100,000 adult population
			Number of ATM per 100,000 adult population
			Number of agents (mobile money) per 100,000 adults
		Penetration	Number of saving accounts per 1,000 adult population
			Wallet account per 1,000 adults
		Usage	Deposit as a percentage of GDP
			Loans as a percentage of GDP
			Value of mobile money transactions as a percentage of GDP
Nizam et al (2020)	Combination of parametric method (PCA) and non-parametric method	Bank Penetration	Number of saving accounts per 1,000 adults
		Availability	Number of ATM per 100,000 adults
			Number of outlets per 100,000 adults
		Usage	Deposit as a percentage of GDP
			Credit as a percentage of GDP
		Digital	Using internet to pay/buy something online per adult people
			Paid utility bills via a mobile phone per adult people
			Made/received digital payments per adult people

Table A5: Continuation

Author(s)	Methodology	Dimensions	Components
Ahmed & Mallick (2017)	PCA	Outreach	Branches per 100,000 adult people
			ATMs per 100,000 adult people
			Branches per 1,000 km2
			ATMs per 1,000 km2
		Usage	Accounts per 1,000 Adult people
Camara & Tusta (2017)	PCA	Access	Branches per 100,000 adult population
			ATMs per 100,000 adult people
			Agent per 100,000 adult people
		Usage	Percentage of adults possessing a minimum of one financial product (account)
			Percentage of adults deposited funds at a financial institution (savings)
			Percentage of adults borrowed money from a financial institution (loan)
		Barriers	Distance
			Affordability
			Documentation
			Lack of trust
Chakravarty & Pal, (2013)	An axiomatic approach	Access	Branches & ATMs per 100,000 adult people
			Branches & ATMs per 1,000 Km2
		Usage	Credit & deposit per 1,000 people
			Average size of loans & deposits (% of GDP per capita)
Mialou et al (2017)	Weighted geometric average; weights derived from factor analysis	Outreach	ATMs per 1,000 Km2
			other depository corporations (ODC) branches per 1000 km2
		Usage	ODCs per 1000 adults for resident household depositors
			ODCs per 1000 adults for resident household borrowers
Sarma (2008, 2016)	UNDP approach: inverse euclidean distance method	Availability	Branches per 100,000 adult people
		Banking penetration	Saving accounts per 1000 adult people
		Usage	Deposits as (share of GDP)
			Loan as (share of GDP)

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