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Constructing a FinTech Adoption Index for BRICS+ Economies: Evidence from Principal Component Analysis

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ABSTRACT

Using Principal Component Analysis (PCA), this study creates a composite FinTech Adoption Index for eleven BRICS+ economies between 2006 and 2024. The index captures key dimensions of financial and digital infrastructure through four indicators: Automated Teller Machines (ATMs) per 100,000 adults, mobile cellular subscriptions per 100 people, fixed broadband subscriptions per 100 people, and individuals using the internet as a percentage of the population. The World Development Indicators (WDI) database is the source of data for every indicator. The BRICS+ economies differ significantly from one another in terms of the development of digital and financial infrastructure, as shown by descriptive statistics. The correlation analysis indicates moderate-to-strong positive relationships among all four indicators, supporting their suitability for PCA. The findings demonstrate a distinct upward trend in FinTech adoption throughout the BRICS+ economies between 2006 and 2024, emphasising the growing contribution of financial infrastructure and digital connectivity to the advancement of financial technology.

INTRODUCTION

FinTech, an abbreviation of "Financial technology", has proven to be one of the fastest growing and most impactful developments in the world of finance in the past few years. Innovations like mobile banking, ATMs, digital payments, etc. have helped to achieve lower trading fees, sustainable development, financial inclusivity and more (Agarwal *et al.*, 2026; Demirguc-Kunt *et al.*, 2018; Ozli, 2018). Due to this, FinTech usage has grown by over 240% in the past decade (Qureshi & Khan, 2026). It is for these reasons that this paper focuses on FinTech adoption and its impact on finance as a whole.

With the ever-increasing importance of issues such as environmental degradation, climate change and the use of non-renewable resources, the financial sector, and more specifically, FinTech institutions might be some of the first to adopt environmentally friendly policies and techniques. FinTech plays a significant role in supporting environmental finance by facilitating investments, improving the monitoring of environmental, social, and governance (ESG) performance, and enhancing access to sustainable financial products (Azmeh & Al-Raeei, 2024). In particular, FinTech has historically promoted CO2 efficiency, food quality grading and low-cost recyclers (Muhammad *et al.*, 2022). As governments and businesses worldwide strengthen their commitments to achieving carbon neutrality and sustainable development goals, understanding the factors that influence FinTech and its relationship with environmental finance has become increasingly important for researchers, policymakers, and financial institutions.

Furthermore, digital platforms enable investors and financial institutions to evaluate risks more effectively, while advanced data analytics improve decision-making. Rapid advances in digital payments, mobile banking, online lending, digital investment platforms, blockchain-based applications, and other technology-enabled financial services have fundamentally altered the ways in which households, firms, and financial institutions access and deliver financial services (Philippon, 2016; Thakor, 2020). The diffusion of these technologies has been particularly important in emerging and developing economies, where fintech can provide alternatives to traditional financial institutions and potentially overcome geographical, infrastructural, and cost-related barriers to financial access. As a result, fintech adoption has become an increasingly important dimension of financial development, digital transformation, and financial inclusion (Azmeh & Al-Raeei, 2024; Ozili, 2018; Sahay *et al.*, 2020).

Traditional banking systems may face difficulties in reaching geographically dispersed populations and low-income households because of the costs associated with physical branches, documentation requirements, and limited financial infrastructure. Digital financial services can reduce some of these barriers by enabling individuals and firms to access financial services through mobile phones and internet-based platforms (Philippon, 2016). Consequently, fintech has increasingly been viewed as a potential mechanism for extending financial access to populations that have historically remained outside the formal financial system (Demirgüç-Kunt *et al.*, 2018; Ozili, 2018).

The growing importance of fintech is especially evident among the BRICS+ economies; Brazil, China, Egypt, Ethiopia, India, Indonesia, Iran, Russia, Saudi Arabia, South Africa, and the United Arab Emirates. The BRICS grouping has historically represented a significant share

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of the world's economic activity, half of the world's population and many emerging-market financial systems, while its recent expansion has increased the geographical and economic diversity of the group. Large populations, widespread mobile-phone use, expanding internet access, and efforts to promote digital payments have created favorable conditions for fintech development in several emerging economies. At the same time, disparities in financial and digital infrastructure remain significant (Zheng *et al.*,2024).

The Global Findex literature demonstrates that access to formal accounts and digital payments differs substantially across countries and population groups, while factors such as income, proximity to financial institutions, and the cost of financial services remain important determinants of financial inclusion (Allen *et al.*, 2016; Demirgüç-Kunt *et al.*, 2018). More recent evidence also emphasizes that digital financial technologies can interact with traditional forms of financial inclusion in complex ways, suggesting that technological availability and actual adoption should be distinguished carefully (Azmeh & Al-Raeei, 2024). Due to these factors, this paper focuses on BRICS+ nations. Additionally, the expansion of BRICS throughout its existence, has increased the number of its members from just 4 in 2006 to 11 full members and 10 partner nations, now rendering many studies, even those as recent as 2023, outdated, leaving a significant research gap (Udeagha & Muchapondwa, 2023).

Despite the growing importance of fintech, measuring its adoption remains a significant empirical challenge. Fintech is inherently multidimensional, and no single indicator can fully capture the extent to which digital technologies have been incorporated into financial activity. Indicators such as digital-payment usage, mobile-money accounts, internet banking, electronic transactions, digital lending, and online financial services capture different dimensions of fintech adoption. These variables are highly correlated, making it difficult to identify the underlying factors that drive sustainable financial development. This measurement problem has important implications for cross-country comparisons. Existing studies frequently focus on particular dimensions of fintech, such as digital payments or mobile financial services (Putrevu & Mertzanis, 2024; Susanto *et al.*, 2022; Thakor, 2020). While these measures are valuable, they may not capture the broader transformation of financial behavior and financial-service delivery. The difficulty is further illustrated by the fact that fintech products differ substantially in their scope, scale, and economic functions, making it difficult to construct a single universally accepted measure of fintech development (Sahay *et al.*, 2020). To avoid this problem, this paper utilises principal component analysis which is a statistical technique that reduces dimensionality and transforms the many interconnected variables into fewer, simpler, non-correlated variables without significant data loss.

Against this background, this study develops a FinTech adoption index for BRICS+ economies using Principal Component Analysis, measuring and examining trends in fintech adoption across the BRICS+ countries over the study period. Rather than relying on a single measure of digital financial activity, the study combines multiple indicators intended to capture different dimensions of fintech adoption. The development of a fintech adoption index also contributes to future studies by providing a potentially useful variable for subsequent economic analysis. A multidimensional measure can be incorporated into future studies examining the determinants and consequences of fintech adoption (Thakor, 2020).

Despite the number of works regarding the subject of fintech, there are still many research gaps that exist, the primary objective of this paper is to fill these gaps by investigating FinTech adoption using Principal Component Analysis. The structure of this paper is as follows: Section 1 presents introduction, followed by literature review in Section 2. Then Section 3 focuses on research methodology, and Section 4 discusses the result findings. Lastly, Section 5 focuses on conclusion of the study.

LITERATURE REVIEW

Existing literature on FinTech has developed a focus on measuring the adoption of FinTech across economies. One of the core problems is that FinTech cannot be easily perceived as a single economic variable. Rather, it comprises several facets such as digital payments, mobile financial services, internet banking, and digital lending. For this reason, researchers are using various indicators according to the specific facet of FinTech under study. Thakor (2020) suggests that technological advancements have significantly altered the way financial services are delivered, making it challenging to define FinTech just by a single indicator. Likewise, Sahay *et al.* (2020) define digital financial development as a multi-faceted phenomenon that can be measured using multiple indicators.

A relatively common measure has been the adoption of digital financial inclusion as a proxy for FinTech development. The Global Findex Database offers internationally comparable indicators on account ownership and digital payments (Demirgüç-Kunt *et al.*, 2018; Demirgüç-Kunt *et al.*, 2022). Individual indicators, however, only reflect certain aspects of FinTech. For example, digital-payment adoption does not necessarily reflect digital lending, mobile banking, or other technology-enabled financial services. Therefore, any single measure could present a partial picture of the level of overall FinTech adoption.

To overcome this drawback, a number of studies have created composite measures that incorporate multiple indicators. For instance, Khan *et al.* (2023) analyze 76 emerging and developing economies with a composite indicator of digital financial inclusion, which incorporates multiple aspects of financial access and digital activity. Cheng *et al.* (2023) also explore the relationship between financial inclusion and FinTech and carbon emissions at the city level in China, applying a digital financial inclusion

index. These studies show that composite measures can identify wider trends of digital financial development than individual measures. However, current indices tend to be built around a specific research question or financial inclusion rather than for general FinTech adoption across a wider range of economies.

One important methodological question arises when constructing a composite index – how to weight the indicators. Equal weighting implies that each indicator plays a similar role in the concept; subjective weighting can add in the researcher's judgment. The OECD (2008) emphasises the need for attention to variable selection, normalisation, weighting and aggregation to build composite indicators. The resulting index and cross-country comparisons can be affected by these decisions. A data-driven weighting procedure can thus be used as an alternative method for weight assignment.

The correlation of FinTech indicators results in an additional measurement challenge. Digital payments, mobile banking, access to the internet, electronic financial transactions, etc. can be related and may evolve in parallel. When variables are highly correlated with each other, treating them independently may lead to redundancy and multicollinearity. The methodology should accordingly seek to identify common information across similar indicators, without undue duplication.

PCA is a suitable solution to this problem. According to Jolliffe and Cadima (2016), PCA projects correlated variables into a smaller number of components that are able to capture as much variance in the original data set as possible. Abdi and Williams (2010) also show how PCA can reduce the number of components needed to describe the information in correlated variables. The benefit of this is that PCA can be used to reduce dimensionality without losing information that is relevant to differences between observations, and can be used to create an index using multiple related indicators.

One of the key benefits of PCA is that it uses data-driven weighting. Instead of giving equal and pre-defined weights, the contribution of each variable is calculated based on the statistics of the data set (Jolliffe & Cadima, 2016). This minimizes subjectivity in the creation of indexes. But the selection of the indicator is still very important even in the absence of PCA. The index that results is based on whether the variables truly reflect the adoption of FinTech. Therefore, it is crucial to identify indicators that reflect different but related aspects of digital financial development.

Past empirical studies also underscore the significance of using such measurement on a transnational level. Research on digital finance has been largely focused on China. The research based on Chinese city-level data mostly reports that digital finance can impact environmental outcomes by means of technological innovation, financing constraints, and better resource allocation (Cheng *et al.*, 2023; Lu *et al.*, 2023; Yang *et al.*, 2023). The results from wider samples of emerging markets, however, are different. In their study on 76 emerging and developing countries, Khan *et al.* (2023) found a positive correlation between digital financial inclusion and carbon emissions. The divergent results indicate that digital finance can affect outcomes differently in various economic structures and technological and institutional contexts.

This is especially important for the economies of BRICS+ due to variations in financial infrastructure, technological capacity, and digital development. While there is some existing evidence regarding particular components of digital finance, less attention has been paid to building a coherent, multi-dimensional FinTech measure that can be used for the larger BRICS+ group. If a common index could be developed, it would enable a systematic comparison of the differences in the level of FinTech adoption between countries and over time.

Overall, the literature suggests that FinTech adoption is multi-dimensional, and that the individual indicators might only partially capture the evolution of FinTech. The studies conducted confirmed the validity of composite indicators but pointed out the indicator selection, correlation, and weighting issues. PCA offers a statistical solution that, besides being statistically valid, retains a significant amount of information from the original data set (Abdi & Williams, 2010; Jolliffe & Cadima, 2016). The present study builds on this literature by using PCA to create a FinTech Adoption Index for the BRICS+ economies, using several indicators related to FinTech. This gives a uniform and data-based benchmark to compare across countries and for future studies that explore the broader impacts of the adoption of FinTech.

MATERIALS AND METHODS

The methodology adopted in this study is quantitative, using Principal Component Analysis (PCA) to create a composite index of the level of FinTech adoption in selected emerging economies. PCA is a multivariate statistical method that minimizes information loss from the original data and projects the variables into a lower-dimensional space that captures the most important information (Jolliffe & Cadima, 2016). The components are linear combinations of the original indicators and are ordered by the variance they explain (Jolliffe & Cadima, 2016). PCA was appropriate as the adoption of FinTech is multidimensional and cannot be fully captured by one indicator (OECD, European Union, & European Commission, 2008). For a complex concept with several measurable dimensions that need to be aggregated into a single indicator, composite indicators can be useful (OECD, European Union, European Commission, 2008). Hence, PCA merges multiple measures of digital financial development into a single composite measure, the FinTech Adoption Index (FTI), which represents a more comprehensive understanding of FinTech adoption (Jolliffe & Cadima, 2016).

The indicators chosen for the PCA span various aspects of the adoption of FinTech and digital financial development. These include having a mobile money account, using digital payments, internet penetration,

mobile-cellular subscriptions, and access to digital financial services. The multiple indicators approach is consistent with composite-indicator methodology, as multidimensional phenomena should be measured and presented by several relevant variables, instead of a single indicator (OECD, European Union, & European Commission, 2008). The Global Findex Database offers internationally comparable data on financial-service usage, such as data on financial inclusion, account ownership, mobile money, and digital payments (Demirgüç-Kunt *et al.*, 2022). Internet usage and mobile subscriptions are examples of digital connectivity variables that can be accessed from the International Telecommunication Union (ITU) (International Telecommunication Union [ITU], 2024). The indicators are suitable because access to finance and technological infrastructure are essential for FinTech (Demirgüç-Kunt *et al.*, 2022). By combining these indicators, PCA is able to reveal the overall aspect of FinTech adoption rather than one specific aspect of digital finance (Jolliffe and Cadima, 2016).

This is helpful due to the fact that variables are often measured in different units, scales, and ranges. Internet penetration can be presented as a percentage value, for instance, and the number of mobile subscriptions per 100 inhabitants. If the scales of variables were not standardized, then the larger scales might have a disproportionate impact on the PCA results (Jolliffe & Cadima, 2016). The standardization is done following standard procedures for creating composite indicators from variables measured in different units (OECD, European Union & European Commission, 2008). This will generate variables having a mean value of zero and a standard deviation of one, thus putting all indicators on a similar scale (Jolliffe & Cadima, 2016). Standardization provides the ability to measure the relationship and not the differences among indicators due to the units used in their original data (OECD, European Union, & European Commission, 2008).

The variables are standardized and then introduced into the PCA procedure, and a correlation matrix is created to look for relations among the selected indicators. The correlation matrix accounts for the relationships between indicators irrespective of their measurement scale as the variables have been standardized (Jolliffe & Cadima, 2016). PCA is then used to break this down into eigenvalues and eigenvectors (Abdi & Williams, 201). Eigenvalues indicate the variance explained by the principal components, and eigenvectors represent the coefficients for the construction of the principal component (Jolliffe & Cadima, 2016) (Abdi & Williams, 2010). PC1 is the linear combination of the standardized variables that accounts for the largest percent of the total variance (Jolliffe & Cadima, 2016). Future components describe the rest of the variation and are not correlated to the previous components (Jolliffe & Cadima, 2016). This converts the original indicators into fewer components, while retaining information from the data set (European Union, 2008).

The number of components retained is based on the eigenvalues, cumulative variance explained and a scree plot and the Kaiser criterion is also used as a rule of thumb. Generally, the Kaiser criterion suggests that components with eigenvalues greater than one be retained, as they have more variance than a single standardised variable (Jolliffe & Cadima, 2016). But it is also important to take into account the percentage of the variance explained and the meaningfulness of the components' interpretations (European Commission, 2008). The largest proportion of total variance is explained by PC1, which is why it is given particular attention in this paper, as it can form a single representation of common variance across the FinTech indicators as thoroughly as possible (Jolliffe & Cadima, 2016). The loadings of the components are checked to see how much each indicator contributes to PC1 (Jolliffe & Cadima, 2016). PC1 can be interpreted as indicating the level of FinTech adoption (OECD, European Union, & European Commission, 2008), as these indicators have positive and strong loadings.

The FinTech Adoption Index (FTI) is based on indicator values that are standardized and coefficients derived from Principal Component Analysis (PCA). is the standardized value of the (k)-th indicator of FinTech (also known as the indicator's characteristic), and (beta_k) is the coefficient obtained by PCA. PCA differs from equal weighting by giving weights based on the statistical contribution of each indicator to the extracted component (European Union, & European Commission, 2008). This decreases the need for internal estimates of the relative significance of the individual indicators (OECD). The higher the FTI score, the stronger the adoption of FinTech, and the lower the score, the weaker the adoption (Jolliffe & Cadima, 2016). The index then takes several interrelated metrics of digital financial development and aggregates them into a single quantitative indicator that can be made comparable across countries and over time (European Union, & European Commission, 2008). The eigenvalues, explained variance, and component loadings are reported to maintain transparency and reproducibility of the index (Jolliffe & Cadima, 2016).

RESULTS AND DISCUSSION

This section presents the empirical findings of the study, which constructs a composite FinTech Adoption Index for the BRICS+ economies over the period 2006 to 2024 using Principal Component Analysis (PCA). The discussion proceeds in five stages: first, the data variables and their sources are described; second, the descriptive statistics of the underlying indicators are reported; third, the correlation structure among the variables is examined to establish their suitability for PCA; fourth, the PCA procedure itself is presented, including the eigenvalues, variance explained, component loadings, and the resulting composite index; and finally, the adequacy of the sample for PCA is confirmed through the Kaiser-Meyer-Olkin (KMO) test.

Data Variables and Definitions

The FinTech Adoption Index is constructed from four indicators, each capturing a distinct dimension of financial and digital infrastructure. The first indicator, ATM, refers to the number of Automated Teller Machines per 100,000 adults and represents the extent of physical, formal banking infrastructure available to the population. The second indicator, MCS, denotes Mobile Cellular Subscriptions per 100 people and captures the reach and penetration of mobile telecommunication networks, which serve as a primary channel for mobile banking and digital payment services. The third indicator, FBS, refers to Fixed Broadband Subscriptions per 100 people and reflects the quality and availability of high-speed internet infrastructure that underpins online financial services. The fourth indicator, INT, measures the share of individuals using the internet as a percentage of the total population and represents the overall level of digital engagement and connectivity within a country. Together, these four indicators provide a comprehensive picture of both the physical and digital infrastructure that enables the adoption of financial technology. All four variables are sourced from the World Development Indicators (WDI) database maintained by the World Bank, and their definitions and sources are summarised in Table 1.

The composite index is constructed for a panel of ten BRICS+ economies, comprising the original BRICS members (Brazil, Russia, China, India, and South Africa) together with five additional economies that joined the grouping (Egypt, Ethiopia, Iran, the United Arab Emirates, and Saudi Arabia). This expanded sample allows the analysis to capture a broader and more diverse range of emerging-market economies, spanning different regions, income levels, and stages of digital financial development. The full list of countries included in the analysis, along with their corresponding country codes, is presented in Table 2.

Table 1: Data Variables, Sources and Explanation

Variable Code	Indicator Name	Source
ATM	Automated Teller Machines (ATMs) (per 100,000 adults)	WDI
MCS	Mobile Cellular Subscriptions (per 100 people)	WDI
FBS	Fixed Broadband Subscriptions (per 100 people)	WDI
INT	Individuals Using the Internet (% of population)	WDI

Source: Author's own construct

Before proceeding to the correlation analysis and Principal Component Analysis, it is necessary to first examine the descriptive statistics of the four indicators. This step provides an overview of the central tendency, dispersion, and range of each variable across the panel of BRICS+ economies over the period 2006 to 2024, and helps to identify whether the data are complete, consistent, and appropriately scaled for further multivariate analysis.

Table 2: List of Countries in the BRICS+ Economies

Country Code	Country
1	Brazil
2	Russian Federation
3	China
4	India
5	South Africa
6	Egypt, Arab Rep.
7	Ethiopia
8	Iran, Islamic Rep.
9	United Arab Emirates
10	Saudi Arabia

Source: Author's own construct

The descriptive statistics for ATM, MCS, FBS, and INT are reported in Table 3. Table 3 reports the descriptive statistics for each of the four variables, summarizing the number of observations, the mean, the standard deviation, and the minimum and maximum values recorded. The

Table 3: Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
ATM	190	56.445	43.901	0.030	184.871
MCS	190	111.275	52.375	1.454	220.412
FBS	190	10.725	11.522	0.0003	47.193
INT	190	50.037	30.242	0.311	100.000

Source: Author's own construct

results show that all four variables have a complete panel of 190 observations, confirming that there are no missing data points across the countries and years included in the study. The variables also exhibit substantial variability: for instance, ATM ranges from as low as 0.03 to as high as 184.87 per 100,000 adults, while INT ranges from 0.31 to 100 per cent of the population. This wide dispersion reflects the considerable diversity in financial and digital infrastructure across the BRICS+ economies and over the sample period. Furthermore, because the four variables are measured on different scales and units (for example, ATMs per 100,000 adults versus the percentage of individuals using the internet), it is appropriate to construct the Principal Component Analysis using the correlation matrix rather than the covariance matrix. This approach standardizes each variable to a common scale before extracting the principal components, thereby ensuring that no single variable dominates the analysis purely as a result of its scale.

Correlation Matrix

Before conducting the Principal Component Analysis, it is important to examine the degree of association among the four indicators. This is because PCA is designed to summarise the shared information, or common variance, across a set of variables; if the variables are not meaningfully related to one another, there would be little shared information for PCA to extract. The first step, therefore, is to assess whether the variables are sufficiently correlated to justify their combination into a single composite index.

The correlation matrix displays the pairwise correlation coefficients between all combinations of the four variables. The correlation coefficient, denoted r, ranges between -1 and +1 and indicates both the strength and the direction of the linear relationship between two variables. A coefficient of +1 represents a perfect positive relationship, meaning that the two variables move in the same direction in exact proportion. A coefficient of 0 indicates the absence of any linear relationship between the variables. A coefficient of -1 represents a perfect negative relationship, meaning that the two variables move in exactly opposite directions. In general, the closer the coefficient is to either +1 or -1, the stronger the relationship between the two variables, whereas values closer to 0 indicate a weaker association.

Table 4: Correlation Matrix

	ATM	MCS	FBS	INT
ATM	1.0000			
MCS	0.5959	1.0000		
FBS	0.5240	0.5638	1.0000	
INT	0.6392	0.8045	0.7888	1.0000

Source: Author's own construct

As shown in Table 4, all pairwise correlations among ATM, MCS, FBS, and INT are positive, ranging from a moderate 0.524 (between ATM and FBS) to a strong 0.805 (between MCS and INT). Internet usage (INT) displays the strongest associations with the other three indicators, correlating at 0.639 with ATM, 0.805 with MCS, and 0.789 with FBS, suggesting that internet penetration moves closely in tandem with mobile connectivity, broadband access, and physical banking infrastructure alike. Mobile cellular subscriptions (MCS) and fixed broadband subscriptions (FBS) are also strongly correlated with one another (0.564), while automated teller machines (ATM) show comparatively weaker, though still moderate, correlations with the remaining three variables (ranging from 0.524 to 0.639). Overall, the correlation matrix reveals moderate-to-strong positive associations among all four variables, with coefficients ranging from 0.524 to 0.805. These relationships indicate that the indicators share substantial common variance, providing preliminary evidence that they are appropriate candidates for combination into a single composite index through Principal Component Analysis.

Principal Component Analysis (PCA)

Having established that the four indicators are sufficiently correlated, the analysis proceeds to Principal Component Analysis, which is used to reduce the four original variables into a smaller number of components while retaining as much of the original information as possible. Central to this procedure is the concept of the eigenvalue, which measures the amount of total variance explained by each principal component. In simple terms, the eigenvalue indicates how much information from the original variables is captured by a given component: the larger the eigenvalue, the greater the share of information that component contains. The eigenvalues, along with the proportion and cumulative proportion of variance explained by each of the four components, are reported in Table 5, and the corresponding component loadings are reported immediately below it.

The results in Table 5a show that the first component (Comp1) has an eigenvalue of 2.969, which is considerably larger than the eigenvalues of the remaining three components (0.502, 0.409, and 0.120, respectively). Applying the Kaiser criterion, which retains only those components with an eigenvalue greater than one, only the first component qualifies for retention. This first component alone explains 74.24 per cent of the total variance across the four variables, a proportion that is considerably high and indicates that it captures the great majority of the information contained in ATM, MCS, FBS, and INT. Consequently, the first principal component was selected as the sole basis for constructing the composite FinTech Adoption Index, as it adequately summarises the shared variation among the original indicators without requiring additional components.

Table 5: Eigenvalues and Variance Explained

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.96942	2.46748	0.7424	0.7424
Comp2	0.50195	0.09309	0.1255	0.8678
Comp3	0.40886	0.28908	0.1022	0.9701
Comp4	0.11978	—	0.0299	1.0000

Source: Author's own construct

Table 6: Component Loadings

Variable	Comp1	Comp2	Comp3	Comp4
ATM	0.4592	0.7437	0.4845	0.0358
MCS	0.5021	0.1440	-0.7295	0.4416
FBS	0.4857	-0.6196	0.4603	0.4102
INT	0.5487	-0.2057	-0.1455	-0.7972

Source: Author's own construct

Table 5b reports the eigenvectors, or loadings, for each of the four variables on each component. The loadings represent the weights assigned to each variable when constructing a given principal component, and therefore indicate how strongly each variable contributes to that component. Focusing on the first component, all four variables display positive loadings, ranging from 0.459 for ATM to 0.549 for INT. This indicates that ATM, MCS, FBS, and INT all move in the same direction along the first component, suggesting that they jointly represent a common underlying construct, namely the level of financial technology adoption. Among the four variables, internet usage (INT) exerts the strongest influence on the first component (0.549), followed by mobile cellular subscriptions (MCS, 0.502), fixed broadband subscriptions (FBS, 0.486), and automated teller machines (ATM, 0.459). Because the loadings are relatively similar in magnitude, this indicates that each variable contributes in a fairly balanced manner to the composite index, rather than the index being dominated by any single indicator. Based on these loadings, the first principal component can be expressed as the following weighted combination of the standardised variables:

$$PC1 = 0.459(ATM) + 0.502(MCS) + 0.486(FBS) + 0.549(INT) \quad (1)$$

This equation represents the composite FinTech Adoption Index used throughout the remainder of the analysis, with each variable entering the index in proportion to its contribution, or loading, on the first principal component.

Scree Plot

A scree plot provides a graphical means of determining how many principal components should be retained for further analysis. It plots the eigenvalue associated with each component against the component number, and the number of components to retain is typically identified by locating the point at which the curve flattens out, commonly referred to as the 'elbow' of the plot. Figure 1 presents the scree plot corresponding to the PCA results reported in Table 5.

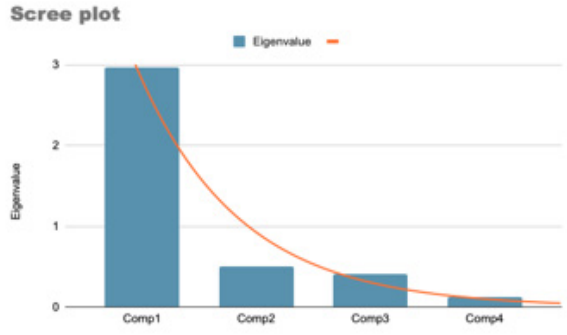


Figure 1: Scree Plot

As shown in Figure 1, the first component has a markedly large eigenvalue of approximately 2.97, while a sharp decline is observed between the first and second components. From the second component onward, the curve flattens considerably, indicating that little additional variance is explained by the remaining components. This pronounced elbow after the first component provides clear graphical confirmation that a single component is sufficient to represent the underlying data structure. This visual evidence is fully consistent with the Kaiser criterion applied earlier, which likewise retained only the first component on the basis of its eigenvalue exceeding one. Taken together, both the numerical and graphical evidence support the decision to base the composite FinTech Adoption Index solely on the first principal component.

Composite FinTech Adoption Index

Using the first principal component identified above, predicted component scores were generated for each country and year in the sample. Because the first component explains 74.24 percent of the total variance across the four underlying indicators, these predicted scores were used as the composite FinTech Adoption Index in the subsequent analysis, providing a single, parsimonious measure of financial technology adoption for each BRICS+ economy over time. Figure 2 presents the evolution of this composite index for the ten BRICS+ economies over the period 2006 to 2024.

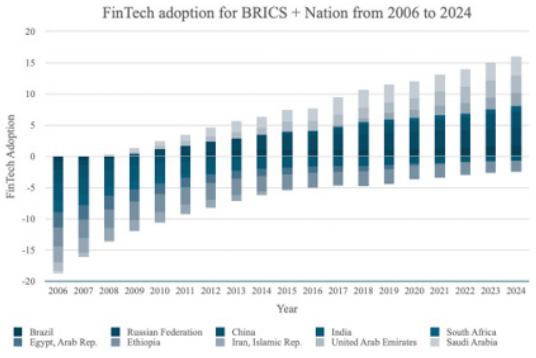


Figure 2: FinTech Adoption Index for BRICS+ Economies, 2006–2024

Source: Author's own construct

Figure 2 illustrates a clear and consistent upward trajectory in the composite FinTech Adoption Index for the BRICS+ economies as a group over the nineteen years under study. In the earlier years of the sample, from 2006 to around 2013, the aggregate index for the panel is negative, reflecting the fact that levels of ATM penetration, mobile subscriptions, broadband access, and internet usage across most of these economies were, on average, below the panel-wide mean during this period. From the mid-2010s onward, however, the index rises steadily and almost without interruption, turning positive by the end of the 2010s and continuing to climb through to 2024. Among the individual economies, the two largest members of the panel by population and economic size, China and India, together with Russia, are visibly among the largest positive contributors to the composite index in the later years of the sample, consistent with the substantial investments these economies have made in mobile and internet infrastructure over the past two decades. Additionally, Saudi Arabia and the United Arab Emirates have shown great improvements between the periods of 2006 to 2024, progressing from weaker positions in the index to much stronger ones. By contrast, several of the other BRICS+ members, including Ethiopia and Iran, contribute more modestly to the overall upward movement, reflecting comparatively slower or more recent gains in digital financial infrastructure. Overall, the figure indicates that financial technology adoption across the BRICS+ grouping has not only increased substantially since 2006 but has also become markedly more widespread and pronounced in the most recent years covered by the data, underscoring the accelerating pace of digital financial transformation across these emerging economies.

Kaiser-Meyer-Olkin (KMO) Test

As a final diagnostic check, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was calculated to confirm that the four variables share sufficient common variance to justify the application of Principal Component Analysis. The KMO statistic indicates whether the variables possess enough shared information to be meaningfully combined into one or more principal components, with values above the conventional threshold of 0.60 generally considered acceptable. The results of the KMO test are presented in Table 7.

Table 7: KMO Test (Kaiser-Meyer-Olkin)

Variable	KMO
ATM	0.9257
MCS	0.7287
FBS	0.7201
INT	0.6565
Overall	0.7317

Source: Author's own construct

As shown in Table 6, the overall Kaiser-Meyer-Olkin measure of sampling adequacy was 0.732, indicating that the data were suitable for Principal Component Analysis. At the individual variable level, KMO values ranged from 0.657 for INT to 0.926 for ATM, with all four variables exceeding the recommended minimum threshold of 0.60. These results confirm that the four indicators share sufficient common variance to justify the application of PCA and lend further support to the validity of the composite FinTech Adoption Index constructed in this study.

Discussion

Based on the results of the Principal Component Analysis, several inferences can be developed on the pattern of financial technology adoption in the BRICS+ economies in the period 2006–2024. Overall, the composite index, component loadings, and country-level trends all point to a broad, infrastructure-driven shift toward digital finance across the panel, though one that has been uneven across countries.

First, the gradual increase in the composite index from negative values in the mid-2000s to positive and rising values by 2024 suggests that the BRICS+ economies, as a group, have moved from a below-average digital and financial infrastructure position to an above-average infrastructure position relative to the panel mean during the sample period. This is consistent with the broader trend documented in the financial inclusion literature where the expansion of mobile networks and internet access in emerging markets over the past two decades has been closely associated with the growth of digital financial services. The consistency and near-monotonic nature of the index increase also implies that this shift has not been driven by short-term or cyclical factors but, rather, reflects a sustained, structural expansion of the underlying infrastructure base.

Second, loadings on the first principal component imply that internet usage (INT) and mobile cellular subscriptions (MCS) are stronger determinants of the composite index than automated teller machines (ATM). This pattern suggests that in this sample, the growth in fintech adoption has been driven largely by mobile and internet connectivity, rather than by the expansion of physical banking infrastructure. This is in line with the wider observation in the fintech literature that mobile-based channels have allowed households and firms in emerging markets to access financial services without relying on traditional brick-and-mortar banking networks. The comparatively smaller, though still positive, contribution of ATM to the index suggests that physical banking infrastructure has continued to expand alongside digital channels, but at a relatively slower pace, reinforcing the interpretation that the digital channel has become the leading edge of financial access in these economies.

Third, the cross-country pattern visible in the index points to a degree of divergence within the BRICS+ grouping. Larger and comparatively higher-income economies, such as China, India, Russia, the United Arab Emirates, and Saudi Arabia, appear to account for the largest share of the increase in the index in the later years of the sample, while economies such as Ethiopia and Iran show a more gradual rise. This divergence suggests that, although the group as a whole has advanced together, the pace of that advancement has not been uniform, and the gap between the fastest- and slowest-adopting economies within the panel may have widened over time rather than narrowed. From a policy perspective, this points to a continued need for targeted investment in digital and telecommunications infrastructure in the lower-adopting economies of the panel if the gap in fintech readiness within the BRICS+ grouping is to be closed.

Finally, the fact that a single principal component was sufficient to explain nearly three-quarters of the total variance in the four indicators, combined with an overall KMO statistic well above the conventional threshold of 0.60, suggests that ATM, MCS, FBS, and INT move together closely enough to be treated as manifestations of one underlying dimension of infrastructure-based fintech readiness, at least within this sample. At the same time, this also implies that the index constructed here captures the infrastructural and access dimension of fintech adoption rather than other dimensions emphasised elsewhere in the literature, such as the depth of actual usage, financial literacy, or the regulatory environment. The composite index should therefore be interpreted specifically as a measure of the physical and digital infrastructure underpinning fintech adoption, rather than as a complete measure of financial inclusion or fintech usage intensity in the BRICS+ economies.

CONCLUSION

This study constructs a composite FinTech Adoption Index for ten BRICS+ economies over the period 2006–2024 using Principal Component Analysis (PCA). The index combines four indicators; ATM availability, mobile cellular subscriptions, fixed broadband subscriptions, and internet usage, to capture the financial and digital infrastructure underlying FinTech adoption. The first principal component has an eigenvalue of 2.969 and explains 74.24% of the total variance, substantially exceeding the explanatory power of the remaining components. Moreover, all four indicators have positive and relatively balanced loadings on the first component, suggesting that FinTech adoption is a multidimensional phenomenon supported jointly by physical banking infrastructure and digital connectivity. Internet usage has the highest loading, followed by mobile subscriptions, fixed broadband, and ATMs.

The overall KMO value of 0.732 confirms the adequacy of the data for PCA. The resulting index indicates a clear improvement in FinTech adoption across the BRICS+ economies between 2006 and 2024. Although the pace of progress differs across countries, the overall upward trend highlights the increasing importance of digital connectivity and financial infrastructure. Thus, the

composite index provides a useful measure for examining FinTech development and its broader economic implications within BRICS+ economies.

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