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Modeling the efficiency of financial inclusion in Bihar: A data envelopment analysis

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Abstract

The study aims to evaluate the effectiveness of financial inclusion in Bihar from 2016-2017 to 2020-2021 and analyze the variations across different districts. The study uses secondary data from the State Level Bankers Committee Report and employs the CCR 1978 model and the Super Radial Efficiency model of DEA to measure overall technical efficiency. The analysis considers 10 indicators representing 4 dimensions of financial inclusion. The study identifies districts with improving financial inclusion levels and identifies efficient districts as benchmarks for others to emulate. Some districts show stagnation or decline, indicating the need for targeted interventions and policy measures. Policymakers can use the efficiency scores to identify districts requiring more support for enhancing financial inclusion. Financial institutions can learn from the practices of efficient districts to improve their services in less efficient areas. The focus on district-level analysis highlights the importance of decentralization in financial inclusion planning and implementation.

Keywords: *Data Envelopment Analysis, Benchmarking, Financial Inclusion, Inclusion Efficiency, technical efficiency, Super Efficiency, Bihar.*
JEL Classification: *G21; G29; C67; O1*

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1. Introduction

Efficiency is crucial for organizations to thrive, aiding in ongoing development, sustainability, and competitiveness. Inclusive finance is vital for economic success, offering resources and savings opportunities, especially for marginalized populations (Kumar et al., 2025; Jaiswal et al., 2024). In India, tailored financial services are essential for broader financial inclusion. Efficiency in financial inclusion means maximizing government resources to enhance access to financial services across the nation, particularly in underserved areas (Kushwaha et al., 2023). Economic growth is connected to increased financial inclusion development (Owen & Pereira, 2018). Financial outreach is frequently viewed as a significant aspect of making financial goods and services accessible to a larger proportion of the public. This is especially important in emerging economies, as such facilities generally exclude large portions of the population, particularly the disadvantaged (Ghosh, 2011).

A sound financial system is very important for any country that wants to have low inflation and long-term growth (Pandey et al., 2025). Financial insecurity, on the other hand, can harm economic development and lower economic well-being (Giri & Bansod, 2019). According to the World Bank Global Findex Survey 2017, the BRICS nations account for around 30% of unbanked adults (1.7 billion worldwide), out of which 11.7% were Indians

(BRICS, 2021). India's financial inclusion score on a scale of 100 is 58, and there were only 14 districts with a CRISIL inclusive score of 100 (CRISIL: An S&P Global Company, 2018).

Assessing financial inclusion alone does not serve the goal of inclusive finance in India. Because India is a country with social, economic, and cultural diversity in which the choice of demand and supply side resources also varies (Jaiswal & Kumar, 2023). There is a need to preserve inclusion sustainability by focusing on the individual demands of each state based on their features to achieve more inclusion, which leads to a decrease in income and wealth disparity (Jaiswal et al., 2024; Kumari & Jaiswal, 2024). The efficiency evaluation for the last few decades was only viewed from the point of organization or enterprises. When it comes to the efficiency evaluation of countries, states, or districts in terms of financial inclusion we have found very little or no literature that focuses on it. The paper introduces a framework of methodology for assessing the extent and effectiveness of financial inclusion in Bihar. The objective of our study is to provide novel aggregate scores of financial inclusion, serving as technical efficiency metrics for each of our Decision-Making Units (DMUs).

They are produced by utilizing the DEA-solver-LV8 (2015-12-05) to solve the DEA (Charnes-Cooper-Rohdes) CCR model (1978) presented in the section below. The primary goal of our research is to examine the financial inclusion level of districts and to rank them considering those levels. Such rankings on DMUs can be performed using aggregate scores. The second objective is to establish the distinction between those DMUs that are efficient. The primary issue lies in establishing a ranking for efficient DMUs, as they all possess identical scores (100%). One way for differentiating efficient districts is to measure their super efficiency, which we interpret here as the number of times they are utilized as a benchmark district for a non-efficient district. As per the report of Census 2011, Bihar was the third-highest populated state of India, with a combined population of 104,099,452.

This study holds importance as it not only covers a state to study financial inclusion but its focus is to highlight the need for inclusion resources for such a vast population, where 89% of the total population was identified as rural.

The remaining section of the paper is structured as follows. In the next section, we have addressed some related literature, the methodology is explained in Section 3, the outcomes we obtained are shown in Section 4, the findings and discussion of this study are discussed in Section 5 and the conclusion of the paper is in Section 6.

2. Literature review

The sustainability of a bank is important for an economy since it enhances and widens the practice of inclusion in a country (Maity & Sahu, 2021; Saha & Ravisankar, 2000; Swain et al., 2017). A study conducted by Muthia et al. (2019) reveals that Financial inclusion has a positive and considerable impact on banking efficiency. Due to intense competition, Debasish (2006) believes that the banking sector's efficiency evaluation has grown its importance. He evaluated the relative effectiveness of Indian banks between 1997 and 2004 using an output-oriented DEA model. His research revealed that new banks proved to be more efficient than old ones. This suggests that modifying the banking system procedure will result in higher efficiency in financial inclusion sustainability. Saha and Ravisankar (2000) asserted that to attain the same growth as international banks in India, commercial banks would need to redefine their competitive business position and develop appropriate business strategies, including risk management. Furthermore, they added that India remained at the bottom of the relative efficiency scales for commercial banks throughout the research period. In order to determine the impact of PMJDY, Maity and Sahu (2020) carried out a study for the pre-introduction period of 2010–2011 to 2013–2014 and the post-introduction period of 2014–2015 to 2017–2018.

They found that there was a significant variation between the public sector banks and between the two periods as well. Maity and Sahu (2021) again conducted a study from 2009-2010 to 2018-2019, where the focus was to know the efficiency of three bank groups in the states of India, where foreign banks were far better than public and private sector banks in terms of efficiency. Maity (2020) visualizes the difference between private and public sector banks over ten years from 2009 to 2018. According to the DEA, public sector banks are found to be less efficient as compared to private sector banks. A study conducted by Yeh (1987) illustrates the drawback of using financial ratios to evaluate performance. He explained how to use the DEA in conjunction with financial ratios to assist Taiwanese bank authorities in distinguishing between efficient and inefficient banks. Mostafa (2007) examined cross-sectional data from the top 50 GCC banks via DEA for the year 2005 in order to emphasize the importance of promoting greater efficiency throughout the GCC banking sector. Halkos and Salamouris (2004) claimed to have used financial efficiency criteria from 1997 to 1999 to assess Greek commercial banks' performance.

As a consequence, they emphasized that greater overall asset size and a reduction in the number of small banks as a result of mergers and acquisitions will contribute to greater efficiency. Emrouznejad and Anouze (2010) employed a mix of classification and regression tree with DEA to determine the causes of efficient and inefficient banking sectors in the Gulf Cooperation Council nations. Grigorian and Manole (2002) applied the DEA model to bank data from various transition nations in order to evaluate measures of commercial bank efficiency.

Evidence currently available indicates that enterprise restructuring and the dominance of foreign ownership increased the efficiency of commercial banks. Further, the efficiency of banking operations improved through consolidation. Consistent with various scholars, Banna and Alam (2020) emphasized the importance of financial inclusion in long-term development. According to the data, Islamic banks' efficiency trends have been erratic in the majority of nations since the global financial crisis. They seek to ascertain how financial inclusion and its connection with GDP development affect Islamic banking efficiency in order to achieve inclusive and sustainable growth.

According to Anh and Nguyen (2019), Bharti and Chitnis (2016) and Nourani et al. (2021), the effective operation of microfinance organizations would result in greater financial inclusion. Microfinance is a critical instrument for increasing access to financial services such as credit, savings, insurance, and remittances. Microfinance achieves operational efficiency to give financial assistance to the unbanked population. On the other hand, the DEA has been used extensively in the literature to evaluate MFIs' efficacy.

Bharti and Chitnis (2016) investigated the relationship between the size and efficiency of MFIs by categorizing them as small, medium, and large. They determined the most efficient MFIs in each area, as well as the average and lowest efficiency of these categories, by utilizing DEA as an analysis method on 89 MFIs. They found a significant relationship between organizational size and efficiency. Nourani et al. (2021) used network DEA analysis and a unique production approach to measure the financial, operational, and outreach efficiency of 90 MFIs from 2013 to 2018. According to the findings, operational efficiency was substantially higher and stayed high among regulated MFIs. Anh and Nguyen (2019) contributed to the examination of the efficiency of microfinance institutions in Vietnam, which are typically efficient with high overall technical efficiency; the efficiency scores have revealed a substantial gap between financial and social performance. Ambarkhane et al. (2020**)** attempted to use DEA to assess the effectiveness of Indian states in reducing poverty. While the efficiency rating in Assam, Bihar, Jharkhand, and Uttar Pradesh varied over the course of the three years, it was consistently inefficient in 2006, 2010, and 2014; in a few other states, such as Kerala, Odisha, Rajasthan, and West Bengal, the efficiency rating changed from efficient to inefficient.

As per Albagoury (2021), the link between growth and poverty was conditional and mostly determined by the state of income distribution in India; that is, if growth was accompanied by a major improvement in distribution, poverty would be reduced. Takouda et al. (2020) performed a study, which was unusual as it intended to analyze the level of financial inclusion in WAEMU nations using a DEA approach. A multidimensional composite index was introduced. The genuine CCR (Constant Return to Scale) DEA model was employed in this experiment. They discovered that between 2010 and 2017, all eight nations consistently raised their participation percentage. Five of the 64 DMUs were found to be relatively efficient, with scores of 100 percent. The other 59 were inefficient. Vong et al. (2014) attempted to fill a vacuum in the research of financial inclusion procedures by conducting a study on women microentrepreneurs in Indonesia and providing benchmarks for financial inclusion programs. Further, stated that financial exclusion has been connected to financial education, rural Indonesian cultural norms, high banking costs, and mobile payments, according to both desk and field studies.

There is no question that many studies have been undertaken to assess the efficiency of financial or banking institutions, but there is little information that compares financial inclusion efficiency at the district or state level. Given the importance of financial inclusion and the emphasis on performance improvement, academics predict that the fundamental DEA models, as well as their various extensions, will play a major role in gauging financial inclusion efficiency. To the best of the author's knowledge, there is limited evidence on the use of the DEA approach in estimating a state's financial inclusion efficiency.

3. Research methodology

3.1 Data

The research is based on secondary data gathered from the State Level Banker's Committee Report. The period of study is from 2016-2017 to 2020-2021, to determine the efficiency level. This research includes all working banks in Bihar, public sector banks, private sector banks, cooperative banks, RRBs, and small financing institutions. Bihar has been chosen for this study due to its persistently low financial inclusion levels, making it a critical case for analysis. The state has the lowest per capita availability of financial services in India, with approximately 17,972 people per bank branch and 16,067 people per ATM—both significantly higher than the national averages (CRISIL, 2018; NCFE, 2018). Despite initiatives like PMJDY, financial exclusion remains prevalent, with only 35% of households having access to formal banking services compared to the national average of 58% (NSSO, 2014). Additionally, Bihar ranks 32nd on the CRISIL Inclusix index and 29th in the NCFE financial education survey, reflecting low financial literacy and inadequate banking penetration (NCFE, 2018). Gender disparities further hinder financial access, as women are less likely to own accounts or use digital financial services (State of the Agent Network, India, 2017). Given these challenges, Bihar serves as a crucial state for studying financial inclusion gaps, barriers, and potential solutions.

3.2 Variables of the Study

To create our suggested composite measure based on DEA, we choose the 10 indicators given in Table 1 based on four criteria, with only indicators related to one key financial service, namely, the bank, taken into account. The researcher wants to claim here that the variables were chosen based on two criteria: relevance and accessibility (Maity & Sahu, 2020). In this context, from the Indian perspective, ATMs as well as bank branches perform a vital role in financial inclusion (Kodan & Chhikara, 2011). The other two variables, the number of Bank Mitra Engaged and the number of training programs organized, have been utilized to quantify financial inclusion for the first time in this study. Any banking system's primary duty is to mobilize money from savings and administer credit, and that is the reason most of the previous research identifies these two factors as financial inclusion indicators (Kodan & Chhikara, 2011; Mahadeva, 2008; Shafi & Medabesh, 2012).

Table 1. Description of the selected financial inclusion indicators

Dimensions	Indicators	Input and Output Model
Availability	No. of Bank Branches (NOBB)	
	No. of ATM (NOATM)	
Accessibility	No. of Bank Mitra Engaged (NOBME)	Input Variables
Awareness	No of Training Program Organized (NOTPO)	
	No. of Accounts Opened by Bank Mitra Engaged (NOAO)	
	Amount Accumulated by Bank Mitra Engaged (AABME)	
Usage	No. of ATM Card (NOATMC)	Output Variables
	Volume of Deposit (VOD)	
	Volume of Credit (VOC)	
	Number of Persons Trained from the Training Program Organized (NOPT)	

3.3 Tools and Techniques

3.3.1 Data Envelopment Analysis

Data Envelopment Analysis (DEA) is defined as a "data-oriented technique" for analyzing the performance of a set of peer entities known as decision-making units (DMUs), which process various inputs into multiple outputs (Cooper et al., 2010). Given the non-parametric computations, the DEA approach may modify numerous outputs while minimizing the requirement for previous knowledge of the relationship between outputs and inputs (Ramanathan, 2003). Although DEA is primarily used to assess the effectiveness of complicated organizations with a variety of inputs and outputs where the conventional approach of performance assessment is impractical (Albagoury, 2021). It is relatively easy to find this ratio if the decision-making unit (DMU) uses a single input to generate a single output, i.e., Efficiency = output/input (Maity & Sahu, 2020).

3.3.2 CCR model of DEA

The DEA has two models. The first was launched in 1978 by Charnes, William Cooper, and Rhodes, who developed its fundamental concept known as the CCR model after their initials. Cooper et al. (2006) assumed DMUs function under constant return to scale. The second was the BCC model developed by Banker, Charnes, and Cooper in the year 1984 which follows a variable (increasing, decreasing, and constant) return-to-scale approach. DEA can be understood in two ways: input-oriented or output-oriented. The output-oriented strategy focuses on achieving the highest possible output with the fewest resources. Because the concept of cost reduction is not implemented according to market conditions, the output-oriented strategy is ideal for inclusive growth efficiency. The researchers employed the CCR model of DEA in 38 districts (DMUs) in Bihar to quantify efficiency with numerous inputs and many outputs.

3.3.3 Super-Radial Model of DEA

To consider the other goal of the article is to examine the levels of financial inclusion of those DMUs that have a 100% efficiency score. The CCR-Output-Oriented Super-Radial model is used to discover super-efficient districts. To differentiate between efficient districts, we have evaluated their super efficiency, which is described as the number of times they function as the benchmark DMU for non-efficient DMUs. The Super Radial DEA (Data Envelopment Analysis) model represents a significant advancement in efficiency evaluation, particularly in cases where traditional DEA models fail to provide a comprehensive ranking of decision-making units (DMUs). This model addresses several limitations of conventional DEA approaches, offering deeper insights into efficiency variations across different sectors (Du et al., 2010). The Super Radial DEA model has been widely used in corporate efficiency analysis, as evidenced by studies in Serbia. Findings suggest that a majority of companies exhibited inefficiencies in 2021, with only a few, such as JP EPS and NIS, achieving efficiency under specific models like SuperBCC-I and SuperBCC-O. The model's capability to highlight areas for improvement—such as optimizing workforce size, business assets, and net profits—makes it an essential tool for corporate performance assessment. This reinforces its utility in strategic decision-making for firms aiming to enhance their operational efficiency (Lukić, 2023). The model has also been instrumental in assessing trade efficiency, particularly in Serbia, where inefficiencies were identified over a prolonged period (2002-2021). By applying the Super Radial DEA approach, researchers have emphasized the need for better management of input-output elements. Additionally, digitalization has been identified as a crucial factor in enhancing trade efficiency. These findings suggest that the model can serve as a valuable instrument for policymakers and businesses aiming to improve the effectiveness of trade operations through technological integration (Lukić, 2023). One of the primary advantages of the Super Radial DEA model is its ability to handle negative data and uncertain input-output conditions (Babazadeh & Pourmahmoud, 2018). Novel adaptations of the model incorporate directional distance functions and interval representations, making efficiency assessments more reliable even in complex scenarios. This feature is particularly beneficial for industries where financial losses, environmental constraints, or fluctuating market conditions create data inconsistencies. The Super Radial DEA model has found applications beyond corporate and trade efficiency, particularly in environmental performance evaluation. By differentiating between radial and non-radial components of inputs and undesirable outputs, the model provides a more refined measurement of eco-efficiency (Afzalinejad, 2021). Its application in China's industrial sectors has underscored the importance of technological advancements in sustaining efficiency improvements. Such insights are crucial for policymakers seeking to balance economic growth with environmental sustainability (Qu et al., 2023). Random mistakes cannot be included in basic models such as CCR-DEA and BCC-DEA. If the various DMUs are efficient, their efficiency value in the basic model is "1," making it difficult to identify their efficiency. As a result, the DMUs' efficiency cannot be accurately evaluated, and only efficient or inefficient may be recognized in the basic DEA model. In the SE-DEA model, an efficient DMU can increase its input based on the ratio while keeping its efficiency (Li et al., 2021). According to Andersen et al. (1993), the low-efficiency port's score stays unaltered under the SE-DEA. Nonetheless, the high-efficiency port's efficiency score may be larger than one, allowing for level allocation.

We are now presenting the actual DEA model that we plan to apply in our study, which is the CCR (Constant Return to Scale) model, first published by Charnes, Cooper, and Rhodes in 1978 and is by far the most often used to date. Talluri (2000) DEA recognizes a set of respective efficient units for each inefficient DMU that can be used as benchmarks for improvement. Further, in DEA multiple inputs and outputs are linearly integrated using weights. The model is detailed further below.

$$virtual\ input = \sum_{i=1}^{I} UiXi \tag{1}$$

where, Xi = represents i^{th} input; I = total number of inputs; Ui = weight assigned to input Xi

$$Virtual\ Output \sum_{j=1}^{J} VjYj \tag{2}$$

where, Yi = represents jth output; J = total number of outputs; Vj = weight assigned to output Yj

$$Efficiency\ DMU = \frac{virtual\ output}{virtual\ input} \qquad = \frac{\sum_{j=1}^{J} VjYj}{\sum_{i=1}^{I} UiXi} \tag{3}$$

Since the efficiency of 38 DMUs must be compared. Using the formula below, let's maximize the efficiency of one of the DMUs, let's say the Mth DMU. The reference DMU in this case is the Mth DMU. The following will be the mathematical equation for the same:

$$\max Em = \frac{\sum_{j=1}^{J} VjmYjm}{\sum_{i=1}^{I} UimXim} \tag{4}$$

Subject to,

$$0 \le \frac{\sum_{j=1}^{J} VjmYjn}{\sum_{i=1}^{I} UimXin} \le 1; n = 1,2,k,n \tag{5}$$

$$Vjm, Uim \ge 0; i = 1,2,K,I; j = 1,2,K,J \tag{6}$$

It has been converted into a linear programming problem in order to assess each DMU's relative efficiency score.

$$\max Em = \frac{\sum_{j=1}^{J} VjmYjm}{\sum_{i=1}^{I} UimXim} \tag{7}$$

Subject to,

$$\sum_{j=1}^{J} VjmYjn - \sum_{i=1}^{I} UimXin \le 0; (n = 1, 2, \dots \dots k) \tag{8}$$

$$\sum_{i=1}^{I} UimXin = 1$$

where, Em is the efficiency of the Mth DMU; Yjm is the jth output of the Mth DMU; Vjm is the weight of that output; Xim is the ith input of the Mth DMU; Uim is the weight of that input, and Yjn and Xin are jth output and ith input, respectively of the nth DMU, n= 1, 2,……N.

Table 2. Descriptive statistics of all the variables

Metric	NOATM	NOTPO	NOBME	NOBB	NOATMC	NOPT	NOAO	AABME	VOD	NOC
N	38	38	38	38	38	38	38	38	38	38
2016-2017										
Mean	177.658	25.2105	400.895	180.105	1238360	720.763	228583	9229.26	737816	276171
St. dev.	235.036	6.39143	203.195	131.483	1164007	147.172	114453	40072.2	1400083	473457
2017-2018										
Mean	180.5	23.6579	394.921	181.737	1216238	615.211	154885	2362.66	823234	334336
St. dev.	231.622	7.79094	190.428	131.781	894666	221.062	90685.5	1487.67	1605581	622009
2018-2019										
Mean	174.079	18.6579	479.737	196.553	1608841	525.158	135694	2034.45	908510	361175
St. dev.	230.27	8.33912	212.269	140.301	963405	252.536	77324.4	1161.33	1783062	638368
2019-2020										
Mean	171.816	116.263	552.474	199.711	1602942	2289.08	256370	11741.5	978375	385457
St. dev.	232.852	148.647	496.083	142.15	937549	2736.85	154570	10031.6	1820276	610871
2020-2021										
Mean	173.895	7.84211	818.289	202	1710443	12506.6	204188	31927.1	1036735	454059
St. dev.	233.849	8.15484	462.666	143.614	999513	74724.5	123342	100042	1946905	761389

Notes:

Bihar's inclusion efficiency is examined by calculating an efficiency ratio equal to a weighted sum of outputs over a weighted sum of inputs. These weights are determined for each DMU by solving an optimization problem in which the efficiency ratio for that DMU is maximized while keeping in mind that the equivalent ratios for all DMUs in the set must be less than or equal to one (Halkos & Salamouris, 2004).

4. Results

We created a CCR DEA model that uses an output-oriented method with four inputs, and the outputs are the six indicators (see Table 1). For a particular year, the DMUs are the districts of Bihar. As a result, Patna2017 as a DMU refers to Patna in the 2016-2017 fiscal year. As a consequence, we have a sample size of 190 DMUs. Because we pooled our panel data into 190 DMUs, our DEA model meets the rule of thumb for obtaining a qualitatively satisfactory model (Takouda et al., 2020). The research is designed to use the DEA approach for measuring technical efficiency, with lower scores of less than 1 indicating inefficiency and higher scores equal to 1 indicating efficiency. Table 2 contains descriptive statistics for all variables. Table 3 and Figure 1 summarise the output-oriented technical efficiency score of all DMUs acquired from CCR DEA throughout five years, beginning from 2016–2017 and ending in 2020–21.

Table 3. Efficiency Score Under the CCR DEA Model

DMUs	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021
Araria	0.9734	0.9934	0.9675	0.9835	1
Arwal	0.9235	1	1	1	0.9982
Aurangabad	0.8318	0.9834	0.97	1	1
Banka	1	0.8034	0.8802	0.7779	0.8516
Begusarai	1	0.8815	1	1	0.9065
Bhagalpur	1	0.8349	0.8178	1	0.7225
Bhojpur	0.8288	0.9584	0.7841	0.9717	0.8636
Buxar	1	0.9293	0.9312	0.9434	0.9702
Darbhanga	0.8164	0.9471	0.9977	0.9872	0.9173
East Champaran	1	1	1	1	1
Gaya	1	1	1	0.9704	1
Gopalganj	0.969	0.9427	0.878	0.9611	1
Jamui	1	1	1	1	1
Jehanabad	0.8875	0.9333	0.8316	1	0.829
Kaimur	1	1	1	1	1
Katihar	0.835	1	0.9744	1	1
Khagaria	0.9731	0.9059	0.813	1	1
Kishanganj	1	1	1	0.9876	1
Lakhisarai	1	1	1	1	1
Madhepura	0.8669	0.9665	1	1	1
Madhubani	1	0.8799	0.9161	1	0.9556
Munger	0.935	1	1	0.9649	1
Muzaffarpur	0.6834	0.97	0.8682	1	1
Nalanda	0.8629	0.9609	0.8627	0.8831	0.9512
Nawada	0.8687	1	1	1	1
Patna	1	1	1	1	1
Purnea	0.9125	0.9535	0.9779	1	1
Rohtas	1	1	1	1	1
Saharsa	0.8314	1	1	1	1
Samastipur	0.9747	1	0.9582	0.9249	0.9257
Saran	1	1	1	1	1
Sheikhpura	1	1	1	1	0.9149
Sheohar	1	1	1	1	1
Sitamarhi	0.8147	1	1	1	1
Siwan	0.939	0.8767	0.9269	1	1
Supaul	0.8376	1	1	1	1
Vaishali	0.8046	0.9793	1	1	1
West Champaran	1	1	1	1	1

The analysis of the efficiency score presented in Table 3 is interpreted in two ways: latitudinal and longitudinal analysis. The latitudinal analysis will describe the growth of financial inclusion over the five financial years of each DMU, and the longitudinal analysis will describe the inclusion efficiency of all the DMUs for each year through a radar chart (Figure 1).

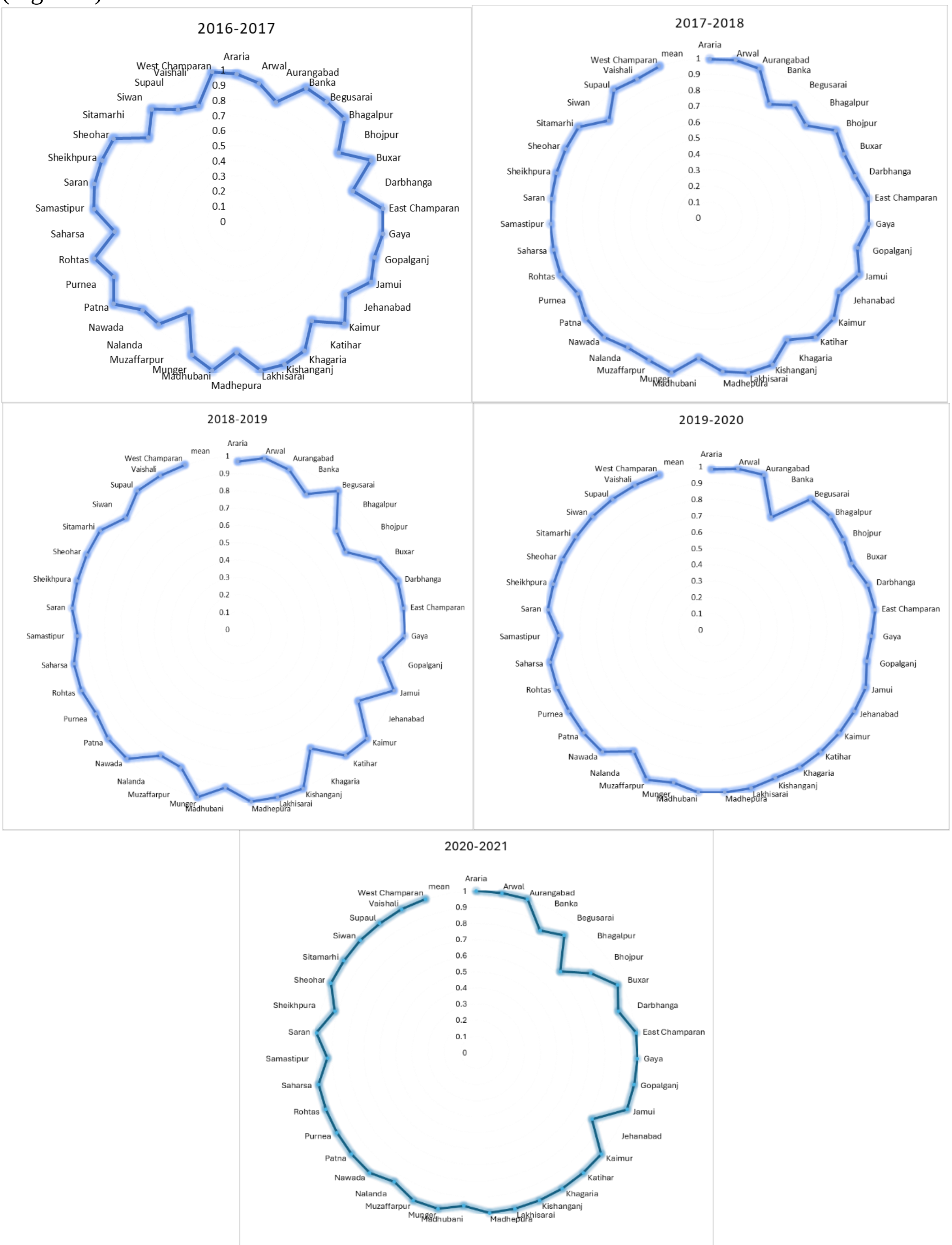

Figure 1. Year-wise technical efficiency score of 38 districts (DMUs) of Bihar

Starting with the latitudinal analysis, there were only nine districts that were 100% efficient for all five years through the CCR DEA efficiency analysis. The districts are East Chamaparan, Jamui, Kaimur, Lakhisarai, Patna, Rohtas, Saran, Sheohar, and West Champaran. Now, through analysis, we have found seven DMUs that are constantly improving their inclusion efficiency score over the years. These are Madhepura, Nawada, Purnea, Saharsa, Sitamarhi, Supaul, and Vaishali. This signifies that the efficiency of these districts has been progressing during these years, and they can increase the scale of operation by effectively utilizing the available resources to achieve sustainable growth. There are 22 districts among all whose efficiency scores are fluctuating over the years. Figure 1 states the graphical representation (longitudinal analysis) of the technical efficiency score of all the DMUs through the CCR DEA model.

From Figure 1, we can observe that in the years 2016-2017, most of the districts are inclined toward the center, which indicates low financial inclusion efficiency. Only seventeen out of thirty-eight districts are efficient, with an efficiency score equal to one. In the year 2017-2018, most of the districts that were inefficient in the previous year moved to an efficiency score of 1 in the next financial year. There are eight districts, such as Arwal, Katihar, Munger, Nawada, Saharsa, Samastipur, and Supaul. A disturbance in the efficiency score has been observed in the financial year 2018-2019. The efficiency scores of Katihar and Samastipur again fell from 1 to 0.9744 and 0.9582, respectively. Most of the districts were efficient in the year 2019-2020, and only eleven were left inefficient. The inclusion efficiency score of Banka continuously decreased over the years and became the lowest in the year 2019-2020 with a score value of 0.7779. In the year 2020-2021, none of the DMUs showed improvement in their efficiency score. In the financial year 2016-2017, seventeen districts were efficient, in 2017-
In 2018, the number of efficient districts rose to twenty, and in the next year, it rose to 21. A major improvement is observed in the number of efficient DMUs in 2019-2020, with twenty-seven DMUs as efficient. The number decreases by 1 in the year 2020-2021. Overall, the DMUs have increased the inclusion and sustainable growth process over the past five years.

High FIE Score (7-10)	• There were only three DMUs falls under high FIE score i.e Rohtas for the F.Y 2016-2017 and Patna for 2017-18 and 2020-21.
Medium FIE Score (4-7)	• Out of 121 DMUs there were total four DMUs comes under medium FIE score i.e Patna for 2016-17 & 2018-19, Saran for 2017-18 and Sheohar for 2020-21.
Low FIE Score (1-4)	• Out of 121 DMUs, 114 DMUs come under a lower efficiency score.

Figure 2. Classification of DMUs based on their efficiency score

The next section covers the second aspect of the objective, where we have emphasized the result of the Super-Radial efficiency model, where we do not find any super-efficient

DMUs. There are 121 out of 190 DMUs that score greater than 1. In Figure 2, we have divided these districts into 3 parts. First, the districts that score between 7-10 come under higher efficiency scores. Second, between 4-7 comes under the medium efficiency score, and last, a score between 1-4 comes under the lower efficiency scores. Out of 121 DMUs, 114 DMUs come under a lower efficiency score. That symbolizes the poor position of the state over the period. Regionally, there are significant differences in efficiency levels between the districts studied. Financial inclusion policies can only enhance input-output efficiency in the short term, which reveals the short-sighted nature of government policymaking.

However, SE-DEA re-analyses the specific efficiency of each effective unit. For instance, Table 4 includes five super-efficient DMUs. As seen from the data, Patna, with the largest amount of input resources, becomes the most efficient DMU among the top five DMUs; Patna acquires a position in the list three times. Apart from the district Patna, Rohtas for the years 2016-2017 has got the highest efficiency score with a value of 17.28. Figure 3 shows the graphical representation of the result.

Table 4. Top 5 efficient DMUs in five year

S.No.	DMUs	Efficiency score	Reference district for non-efficient districts
1	Rohtas17	17.28	26
2	Patna21	8.29	24
3	Patna18	8.09	19
4	Patna19	6.54	19
5	Saran18	6.35	19

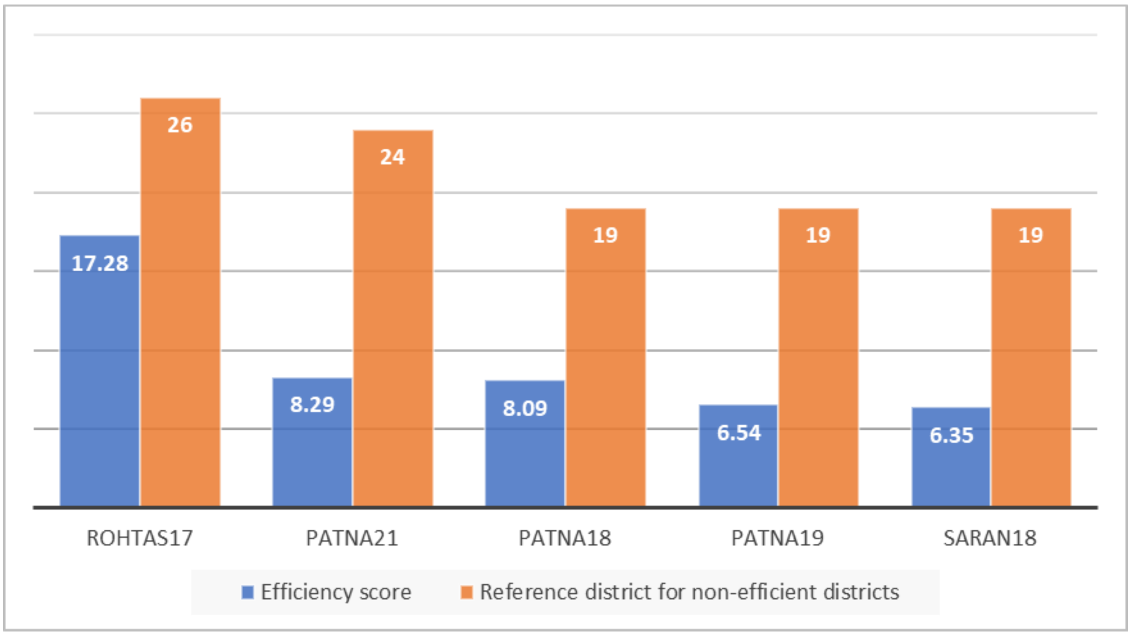

Figure 3. Graphical Presentation of reference DMUs for non-efficient DMUs

5. Findings and Discussion

We have divided our results into two parts, the first based upon the technical efficiency score and the second based upon the super radial model of DEA. From the result of the technical efficiency score, we have found that Patna, with a larger number of input resources for ATM and bank branches, is efficient for all five financial years and achieved the highest efficiency score in the super-efficient model. Further, districts Kaimur, Saran, and West Champaran, despite having fewer resources as compared to Samastipur, Munger, Saharsa, Muzaffarpur, and Gaya, are efficient with a 100% efficiency score. This connotes that efficiency is not limited to resource availability only. Rather, it depends on the efficient usage of resources, where other things are given. However, when we dilute the condition of "other things given", i.e., social, cultural, and administrative factors working behind the reported performance of districts in Bihar, can act as the subject matter for another research. Further, proper utilization of available resources by each district can only be ensured when the executives designated for the program are equally qualified and dedicated to their responsibility. In line with this result, districts that are facing frequent fluctuations in their efficiency score may be the outcome of the random performance of banking activities, systemic efficiency of leadership, regime changes of the government, or leader-specific growth in that area. Sixteen districts are either efficient or have increased efficiency scores over the years. This can also be the continuous effect of the Pradhan Mantri Jan Dhan Yojana (PMJDY) launched in the year 2014, and after the effect of demonetization, which occurred in 2016. A significant contribution can be observed through the implementation of the PMJDY scheme and demonetization. A positive trend is found in deposit accounts, volume of loan disbursement to new accounts, and many household deposits increased, respectively.

We have divided the DMUs into three parts: high, medium, and low super-efficient DMUs, based on the results of the super radial efficiency model of DEA. These districts have a score greater than one. We have found the top five districts that are overall efficient for the five financial years. Patna, as the capital of Bihar, takes the position at the top with the highest number of resources. Districts Saran and Rohtas, which are closer to Patna, might have the advantage of the improved workforce, close monitoring, moral pressure, advantage of administrative headquarters, and accounting supervision, which help them to be in the top five super-efficient districts. Results of the technical efficiency score and super radial model of DEA might seem contradictory, as in the former case, we can see the continuous improvement of efficient districts over the years, and in the latter case, we observed that 63.68% of the total (190) DMUs come under the low financial inclusion category. Randomness and chance factor are observed in the result of the super radial model because here we worked on pooled data that covers a year's time span. Clustering of quality human resources, in charge of the execution of the inclusion program, and the reshuffling of the administrative setup, may be the reason behind it. Therefore, we can say that the inclusion drive should work on the standard operating procedures and standard monitoring of the execution of the program. So that the reshuffling shock to the performance may be insulated. It is our hunch, which may be established by other research, that qualified and dedicated teams might be clustering in and around the capital districts of the state. It will result in a surplus of resources in the periphery of the districts. Further, we would like to add that clustering of talent is reflected in the skewed distribution of efficiency scores, which may be addressed by an explicit and transparent common pool of supervising standards for the purpose at the district level. Inefficient districts can adopt several targeted strategies to enhance their financial inclusion efficiency by emulating the practices of efficient districts. One of the primary strategies is optimizing resource utilization by ensuring the effective deployment of banking infrastructure, including ATMs, bank branches, and business correspondents, to improve outreach and accessibility. Districts that have shown consistent improvement, such as Madhepura, Nawada, and Vaishali, highlight the significance of scaling up financial services through financial literacy programs, digital banking adoption, and microfinance initiatives. Additionally, the fluctuations observed in efficiency scores indicate that financial inclusion efforts often remain short-term. To address this challenge, districts with lower efficiency should implement long-term policy measures focused on sustainable banking models, improved credit access, and stronger regulatory frameworks to maintain consistent progress. The role of digitalization and fintech solutions is also crucial in bridging the financial inclusion gap, as efficient districts have benefited from increased adoption of mobile banking and digital payment systems. Therefore, inefficient districts should leverage financial technology innovations to enhance accessibility and ease of transactions.

Furthermore, strengthening financial literacy campaigns is essential, as a lack of awareness remains a key barrier to inclusion. Encouraging individuals to use formal financial services and educating them on digital transactions can contribute significantly to higher efficiency scores. Institutional support also plays a critical role in financial inclusion, and inefficient districts should establish stronger collaborations with banking institutions, cooperative societies, and self-help groups to expand service penetration. Regional disparities in financial inclusion efficiency highlight the need for localized policy interventions tailored to each district's specific needs. Incentivizing banks to operate in underserved areas, providing subsidies for digital banking infrastructure, and introducing community-based financial initiatives can help bridge this gap. Lastly, enhancing banking infrastructure and outreach remains vital, as the presence of well-established financial networks in efficient districts has contributed to their superior performance. Expanding banking networks, increasing ATMs and financial kiosks, and ensuring last-mile connectivity can significantly improve financial accessibility in lagging districts. By implementing these strategies, inefficient districts can strengthen their financial inclusion framework, leading to overall sustainable growth in the state.

6. Conclusion

This study combines efficiency and super-efficiency methods to evaluate the most representative districts among 38 districts in Bihar for five financial years from 2016-2017 to 2020-2021. An increased focus on excess and unequal distribution of input resources affects the efficiency of financial inclusion. A state can increase its inclusion efficiency score either by optimum utilization or rational distribution of the available resources. Therefore, Bihar's inefficient districts should also seek more ways to improve the efficiency and productivity of the financial inclusion process and maximize their interest. The DEA analysis result shows that overall, nine districts are efficient for all five years. The Bihar financial inclusion efficiency is low because there are no super-efficient districts. The implementation of policy and other government interventions has determined the growth process of financial inclusion in these five financial years. Further, districts that are located adjacent to the capital of the state may benefit from several geographical advantages. Strategic deployment of policies is required in inefficient districts to perform better. The importance of using Data Envelopment Analysis as a tool to discover the process of efficiency can also be reflected in many ways. It can describe the spot of wastage, the projected or needed resources in districts where there is a shortage, and can be helpful for the government to do the needful where it is necessary. The findings of this study underscore the critical role of efficient resource utilization, digital banking adoption, and targeted policy interventions in enhancing financial inclusion across districts. The variations in efficiency scores over time highlight the short-term impact of existing policies, emphasizing the need for long-term, sustainable financial inclusion strategies. Policymakers must focus on strengthening financial infrastructure, promoting digital financial services, and enhancing financial literacy to ensure inclusive growth. The study also reveals significant regional disparities in efficiency, suggesting that a one-size-fits-all approach may not be effective. Instead, localized strategies, such as incentivizing banks to expand services in underserved areas and leveraging fintech solutions, should be prioritized. The policy implications of these findings are crucial for fostering financial stability and economic development in Bihar. By addressing inefficiencies and implementing data-driven financial inclusion strategies, policymakers can create a more inclusive and resilient financial ecosystem that benefits all sections of society.

Like any other study, the present study has a few limitations that warrant more research. This study is limited to only four dimensions. The quality of financial access and mobile banking can also be considered a point of research in the future. Here we used the CCR output-oriented model of DEA; other models of DEA can also be useful in reflecting the current efficiency growth in a state. The research is limited to Bihar only.

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