International Journal of Accounting, Business and Finance (e-ISSN 2583-2123)

IAA Patna Branch

Derivation of weight for measuring financial inclusion index using a non-parametric analysis approach: A study based on Bihar

Prashant Ranjan (Corresponding author)
Department of Management Studies, Jamia Millia Islamia, New Delhi, India
prasshant0005@gmail.com

Akanksha Chaurasia
Department of Psychological Sciences, Central University of South Bihar, Gaya, India
achaurasia705@gmail.com

Abstract

To address the criticism of arbitrary weight selection in current approaches, this paper generates a composite Financial Inclusion (FI) Index to evaluate financial inclusion across 38 districts in Bihar, India, for the financial year 2020–2021. Financial inclusion is assessed through four dimensions: availability, accessibility, awareness, and usage of financial services, incorporating novel indicators such as training programs organized, persons trained, Bank Mitra engaged, and amount accumulated by Bank Mitra. A two-stage Data Envelopment Analysis (DEA) is employed to derive data-driven weights, supplemented by a comparison with the United Nations Development Programme (UNDP) approach, using data from the state-level banker's committee report. The DEA results reveal that 27 districts are efficient (score of 1), while Sheikhpura scores the lowest (0.2727). The UNDP approach classifies 19 districts as high FI (>0.6), 16 as medium (0.4–0.6), and 3 as low (<0.4), with Patna achieving the highest score (0.940) and Arwal the lowest (0.377). By pointing out areas needing intervention, the proposed FI Index improves policy development and is simple to compute and comparable throughout regions. This study advances a strong, scientifically sound instrument for measuring financial inclusion with possible use in many spheres.

Keywords: *Financial Inclusion, Measuring Financial Inclusion, Financial Inclusion Index, Weight Determination, Bihar.*
JEL Classification Codes : G2, G21, G28, G29, O1

Suggested Citation:
Ranjan, P. & Chaurasia, A. (2025). Derivation of weight for measuring financial inclusion index using a non-parametric analysis approach: A study based on Bihar. *International Journal of Accounting, Business and Finance*, 3 (2), 36-48. https://dx.doi.org/10.55429/ijabf.v3i2.167

1. Introduction

Financial inclusion has become a pivotal focus for emerging economies, particularly in addressing the needs of underserved populations, such as those in low-income and rural areas. Globally recognized as a cornerstone of sustainable economic development, financial inclusion strengthens financial systems and fosters broader economic and social progress (Luo et al., 2022; Tram et al., 2021). By enabling access to financial services, it empowers individuals and communities, supporting inclusive growth (Siddiqui & Siddiqui, 2020b). However, these benefits are often more pronounced in developed nations, where financial infrastructure is robust. In developing and underdeveloped countries, significant portions of the population, including vulnerable groups like women, struggle to access formal financial systems due to products ill-suited to their needs, such as lack of credit history or financial education (Jaiswal & Pandey, 2025; Kumari & Jaiswal, 2024; Danquah et al., 2021; Ambarkhane et al., 2022). This disparity underscores the urgent need for inclusive financial systems tailored to diverse populations to drive equitable economic development and ensure long-term sustainability (Pandey et al., 2025).

Difficulties in measuring financial inclusion and designing appropriate interventions exacerbate the challenge of achieving it. According to Sarma and Pais (2008), robust assessment is critical to understanding the extent of financial inclusion and guiding effective policies. However, research shows that there are not many studies using strong, data-based methods to create financial inclusion indices, and many of these studies use random weight assignments that make the results less trustworthy. Additionally, traditional financial products often fail to address the unique circumstances of marginalized groups, such as rural residents or small businesses, limiting the impact of inclusion efforts (Danquah et al., 2021). Emerging solutions like Digital Financial Inclusion (DFI), which leverages technology to provide low-cost, efficient services to disadvantaged populations, offer promising avenues to bridge these gaps (Xia & Xu, 2025). These challenges highlight the need for innovative, context-specific approaches to measure and promote financial inclusion effectively. Thus, research is required to determine the weights that emerge from the data and distinguish themselves from methodologies that suffer from various flaws. Therefore, we must measure financial inclusion to understand the impact of various dimensions and strategies' future activities. This subject has captured the attention of scholars, decision-makers, and governmental bodies, and it acts as the motivation for the present research.

This research adds to existing literature by developing a new composite Financial Inclusion (FI) index that thoroughly assesses the level of financial inclusion across 38 districts in Bihar for the years 2020 to 2021. We used a two-step method called data envelopment analysis to find the right importance for different parts and specific measures that evaluate how financially included people are. Overall, our financial inclusion index improves upon existing indices by utilizing data envelopment analysis (a non-parametric method), thereby addressing researchers' concerns regarding arbitrary weight selection and the lack of scientific rigour seen in earlier studies. Additionally, this research defines financial inclusion using four distinct dimensions (availability, accessibility, awareness, and usage) to enhance comprehension of the concept. Finally, this study adds the number of training programmes organised, the number of persons trained in the training programme, the number of bank mitras engaged in each district, and the amount accumulated by BME as new indicators that hold importance in the underdeveloped state for calculating the overall financial inclusion index.

This paper aims to create a financial inclusion index for 38 districts in Bihar, focusing on the determination of weights for the composite index and exploring the concept of perfect substitutability among the dimensions. To answer the main research questions, two indices are calculated: one by following the Data Envelopment Analysis (DEA) technique, and the other by following the United Nations Development Programme (UNDP) approach based on the weights derived from the data (Kushwaha et al., 2023b). The paper uses data envelopment analysis for the construction of the financial inclusion index, which is based on criticism of the existing methodology and offers a new method of doing the same that is more reliable and applicable.

The rest of the paper is organised as follows: Section 2 reviews the literature related to the method employed for index calculation. Section 3 outlines the research methodology used. Section 4 offers results and a discussion of the findings. The concluding section of the paper puts forward potential future extensions of the work and explores policy implications.

2. Literature Review

Financial inclusion is measured using a variety of metrics since it is a multidimensional concept of financial development. Sharma (2016) evaluates financial inclusion by focusing on three aspects: the penetration of banking institutions, the accessibility of banking services, and the subsequent utilization of these services. Measures of financial inclusion include 5 parameters, which are formal accounts, formal savings, formal credit, possession of a debit card, and usage of the debit card (Dar & Ahmed, 2020). Siddiqui and Siddiqui (2020a) conducted tests to determine whether there is a significant effect of awareness, ability, and usability of mobile phones on the awareness, ability, and usability of banking services. Yadav and Sharma (2016) showcased in their study forms of financial inclusion such as price, condition, access, marketing, and self-exclusion. The researcher wants to claim here that the variables were chosen based on two criteria: relevance and accessibility (Maity & Sahu, 2020). From the Indian viewpoint, the branches and Automated Teller Machines (ATMs) of a bank play a significant part in promoting 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. The main function of any banking system is to gather funds from savings and distribute credit, which is why many past studies consider these two factors as indicators of financial inclusion (Kodan & Chhikara, 2011; Mahadeva, 2008; Shafi & Medabesh, 2012).

Although the importance of financial inclusion is generally recognized, there has yet to be a consensus on how it ought to be assessed. In the literature, various approaches to assigning weights that are not ambiguous and biased have been proposed. One of the first efforts is made by Camara and Tuesta (2014) to use principal component analysis to assign weights that are not based on the researcher's intuition.

This work focuses on the absence of a robust, data-based approach measuring financial inclusion using indicators relevant to areas like Bihar and devoid of random weight assignments. Current research mostly depends on parametric techniques, such as principal component analysis, which imposes limited assumptions, or non-parametric methods, like the UNDP approach, which lacks scientific rigour because of subjective weight selection. Few studies also address the socioeconomic issues of underdeveloped states, so they exclude important indicators like training programs and Bank Mitra involvement that are necessary to evaluate financial inclusion in such environments. By means of a two-stage data analysis approach to identify significant factors and by including new, region-specific measures, this study closes these gaps and enhances the credibility and value of the financial inclusion index.

Listing below (Table 1) some literature and their methodological drawbacks that use UNDP (non-parametric approach), where weights are assigned based on researcher intuition, and some use principal component analysis (Parametric approach), where weights are derived from the data.

3. Research Methodology

3.1 Choice of Variables

In each dimension of financial inclusion, many variables may be theoretically relevant. However, data for a number of these variables are frequently unavailable. Each dimension is measured using proxies. The availability dimension is usually defined using the number of ATMs and bank branches. Indicators to measure accessibility are the number of banks Mitra engaged. Awareness is measured by the proxy variable called the number of training programs organized. Different indicators are employed to theoretically define the usage dimension. These indicators are classified as the number of ATM cards, the number of accounts by bank Mitra engaged, accounts accumulated by bank Mitra engaged, the volume of deposits, the volume of credit, and the number of persons trained from the training program organized.

3.2 Data

We sourced the study data from the state-level banker's committee report for 2020-2021 in 38 districts of Bihar. Our sample list includes all the districts of Bihar. Bihar was chosen for this financial inclusion study because it is among India's poorest, mostly rural states with low financial inclusion rates, high poverty, and limited banking access. Coupled with thorough 2020-2021 district-level data, its prominence in national projects like PMJDY and the Bank Mitra model makes it perfect for testing a new FI Index. The 38 districts of Bihar allow intra-state analysis, thereby addressing research gaps and providing policy-relevant insights for underdeveloped areas. We select research data for 2020-2021 to ensure the data is up-to-date and includes consistent representative variables.

Table 1. Literature Review

Author Date	Title	Methodologies	Methodological Limitations
(Sarma & Pais, 2011)	Financial Inclusion and Development	UNDP approach	Adopted weights subjectively and loss of country-specific information.
(Bozkurt et al., 2018)	Spatial Determination of Financial Inclusion Over Time	UNDP approach	Weights were determined by averaging out the coefficient of variation.
(Yadav et al., 2021)	Multidimensional Financial Inclusion Index for Indian States	UNDP Approach	Equal weights are assigned to each dimension.
(Goel & Sharma, 2017)	Developing a financial inclusion index for India.	UNDP Approach	Equal weights are assigned to each dimension.
(Gupte et al., 2012)	Computation of financial inclusion index for India	UNDP Approach	Equal weights are assigned to each dimension.
(Kodan & Chhikara, 2013)	A theoretical and quantitative analysis of financial inclusion and economic growth	UNDP Approach	Silent for weight determination
(Sethy, 2016)	Developing a financial inclusion index and inclusive growth in India	UNDP Approach	Silent for weight determination
(Sarma, 2008)	Index of financial inclusion	UNDP Approach	Subjective weights according to the availability of data
(Sarma & Pais, 2008)	Financial inclusion and development: A cross-country analysis	UNDP Approach	Subjective weights according to the availability of data
(Ambarkhane et al., 2016)	Developing a comprehensive financial inclusion index	UNDP Approach	Judgemental weights
(Zhu et al., 2021)	Constructing a financial conditions index for the United Kingdom: A Comparative Analysis	Two-step principal component analysis	Using Principal Component Analysis (PCA) needs a high correlation between the variables.
(Nguyen, 2020)	Measuring financial inclusion: a composite FI index for the developing countries	Two-step principal component analysis	Using PCA needs a high correlation between the variables.
(Camara & Tuesta, 2014)	Measuring Financial Inclusion: A Multidimensional Index	Two-step principal component analysis	Using PCA needs a high correlation between the variables.
(Tram et al., 2021)	Constructing a composite financial inclusion	Two-step principal component analysis	Using PCA needs a high correlation between the variables.
(Zulaica Piñeyro, 2013)	Financial Inclusion Index: Proposal of a Multidimensional Measure for Mexico	Principal component analysis	Using PCA needs a high correlation between the variables.
(Amidzic et al., 2014)	Assessing Countries' Financial Inclusion Standing – A New Composite Index	Factor Analysis	Required a larger number of variables and using factor analysis grouped similar variables into a single factor

Note: The above table presents some literature and their methodological drawbacks that use UNDP (non-parametric approach)

3.3 Research Models

3.3.1 Data Envelopment Analysis

DEA is described as a "data-driven approach" for evaluating the performance of a set of comparable entities referred to as decision-making units (DMUs), which convert various inputs into several 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; Kushwaha et al., 2023a). Determining this ratio is quite straightforward when the decision-making unit (DMU) utilizes one input to yield one output, meaning that Efficiency is calculated as output divided by input (Maity & Sahu, 2020).

The DEA consists of two models. The first model was introduced in 1978 by Charnes, William Cooper, and Rhodes, who created the foundational concept known as the CCR model, named after their initials. (Cooper et al., 2006) proposed that DMUs operate under a 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 interpreted in two manners: focused on inputs or focused on outputs. 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 model is detailed further below.

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

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

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

Yi = represents j^{th} output
J = total number of outputs
Vj = weight assigned to output Yj

$$Efficiency\ DMU = \frac{virtual\ output}{virtual\ input} \tag{3}$$

$$= \frac{\sum_{j=1}^{J} VjYj}{\sum_{i=1}^{I} UiXi} \tag{4}$$

Since there are 38 DMUs whose efficiencies need to be evaluated, we will select one of the DMUs, referred to as the Mth DMU, and aim to optimize its efficiency using the formula provided below. In this context, the Mth DMU will serve as the benchmark DMU. The mathematical problem for the same will be: -

$$\max Em = \frac{\sum_{j=1}^{J} VjmYjm}{\sum_{i=1}^{I} UimXim} \tag{5}$$

Subject to,

$$0 \le \frac{\sum_{j=1}^{J} VjmYjn}{\sum_{i=1}^{I} UimXin} \le 1; n = 1,2,k,n \tag{6}$$

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

In order to assess the efficiency score of each DMU, it has been converted into a linear programming problem.

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

Subject to,

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

$$\sum_{i=1}^{I} UimXin = 1 \tag{9}$$

where,
Em is the efficiency of the M^{th} DMU,
Yjm is the j^{th} output of the M^{th} DMU,
Vjm is the weight of that output
Xim is the i^{th} input of the M^{th} DMU,
Uim is the weight of that input, and
Yjn and *Xin* are j^{th} output and i^{th} input respectively of the n^{th} DMU, n= 1, 2……N

3.3.2 UNDP Approach

The other objective of the study is to develop an inclusion index following the non-parametric method (UNDP Approach). The initial phase of this method is to construct sub-indices for each dimension for each district in a specific year. In this phase, the focus is to identify the minimum and maximum values for each indicator to convert their varying measurements and sizes into a standardized scale ranging from 0 to 1. (Sarma, 2008) In n-dimensional Cartesian space, a dimensional index can be thought of as a point. The distance between this location and the ideal point in n-dimensional space is used to calculate IFI.

The following formula is applied to each of the indicators: -

$$D_d = \omega_{d * \frac{A_d - m_d}{M_d - m_d}} \tag{10}$$

Where W_d = Weight attached to the dimension d, 1≥ wd ≥ 0;
A_d = Actual value of dimension d;
m_d = Minimum value of dimension d;
M_d = Maximum value of dimension d;
D_d = Dimensions of financial inclusion d.

Equation (10) confirms that 1 ≥ wd ≥ 0, which here is the nth dimension of financial inclusion represented by the point X = (1, 2, 3…). There are two important factors in calculating a state financial inclusion index. Ideal point W and worst point 0. This Financial Inclusion Index (FII) marks the point of financial inclusion. This will help you determine if your district's financial inclusion is low or high. The larger the gap between 0 and X, high would be the financial inclusion of the district, and the smaller the gap between 0 and X, the lower would be the financial inclusion of the district.

$$x_1 = \frac{\sqrt{d_1^2 + d_2^2 + d_3^2 + \cdots d_n^2}}{\sqrt{\omega_1^2 + \omega_2^2 + \omega_3^2 + \cdots + w_n^2}} \cdot \tag{11}$$

$$x_2 = \frac{1 - \sqrt{(\omega_1 - d_1)^2 + (\omega_2 - d_2)^2 + (\omega_3 - d_3)^2 + \cdots + (w_n - d_n)^2}}{\sqrt{\omega_1^2 + W_2^2 + \omega_3^2 + \cdots + \omega_n^2}} \tag{12}$$

$$FII = \frac{1}{2}(x_1 + x_2) \tag{13}$$

Equation (11) of the FII represents X1 as the average Euclidean distance from 0 to X. A higher value of X1 indicates greater financial inclusion. The inverse Euclidean distance between X and W is expressed by equation (12), but X2 is also relevant to FII. Equation (13) calculates the simple mean of X1 and X2. Another important step in creating an index is dimension weighting. Weights of the dimensions are derived through the non-parametric technique of efficiency evaluation, i.e., the weighted slack-based measure of DEA discussed below. These weights are data-oriented weights, unlike other methods that require some assumptions to be fulfilled. The bad situation of the district will be indicated by point (0,0,0), which means complete financial exclusion, and the perfect situation is indicated by point (1,1,1), which means complete financial inclusion (Goel & Sharma, 2017).

Districts are categorized as follows depending upon the value of IFI calculated: -
An index $\geq$ 0.6 indicates high financial inclusion.
An index with a value between 0.4 to 0.6 indicates medium financial inclusion.
An index $\leq$ 0.4 indicates low financial inclusion.
Finally, after constructing an index for each district, we ranked the 38 districts of a state.

4. Results and Discussion

4.1 Descriptive Statistics

Table 2 below presents descriptive statistics about the indicators we use to measure financial inclusion. Four dimensions (availability, accessibility, awareness, and usage) use ten indicators to measure financial inclusion, where we use mathematical linear programming to describe the order corresponding to each dimension.

Table 2. Descriptive statistics of the input and output variables

	ATM	NOT PO	BME	BB	ATM Card	NOPT	NOA	AABME	VOD	VOC
Max	1509	27	1959	933	5628024	863	467036	78319	12605546	4944284
Min	26	1	144	45	195214	10	33288	1350	96228	53454
Avg	173.895	7.84	818.28	202	1710443	221.5	214708	17034.7	1036735	454059
SD	233.849	8.15	462.66	143.614	999513	230.736	128169	17510	1946905	761389

Source: *Author's Calculation*
Note: NOTPO: Number of Training Programs Organized; BME: Bank Mitra Engaged; BB: Bank branches; NOPT: Number of Persons Trained; NOA: Number of Accounts; AABME: Amount Accumulated by Bank Mitra Engaged; VOD: Volume of Deposits; VOC: Volume of Credit

4.2 First Stage of Weight Determination

For each decision-making unit, we created the virtual input and output using weights.
Virtual input = *viXio* + • • • + *VmXmo*
Virtual output = *uiyio* + • • • + *UsYso*

We then attempted to establish the weights by employing linear programming to optimize the ratio.

The optimal weights may differ from one DMU to the next. As a result, rather than being fixed in advance, the "weights" in DEA are derived from the data. Each DMU is given the best set of weights, which may differ from one DMU to the next.

The Weighted Slack-Based Model (WSBM) is an extension of Data Envelopment Analysis (DEA) that assesses the comparative efficiency of decision-making units through linear programming (DMUs).

Each DMU in DEA is determined based on its inputs and outputs to determine which units are running the most efficiently. Traditional DEA methods, on the other hand, do not account for the importance of various inputs and outputs.

WSBM addresses this limitation by introducing weights for each input and output, which reflect the relative importance of each variable in the analysis. The model also allows for the inclusion of slack variables, which measure the unused resources or excess outputs of each DMU.

By incorporating weights and slack variables, WSBM provides a more nuanced evaluation of DMU efficiency, as it allows for a more accurate assessment of the relative importance of each input and output. Additionally, WSBM can be used to identify areas where a DMU can improve its efficiency by reallocating resources to different inputs and outputs.

As a result, we exclusively consider the primary solution of WSBM for establishing the weights of every input and output. This choice of weight indicates that the significance of the output r is directly related to its contribution to the overall magnitude. Similarly, the weights for the inputs can be ascertained in the same manner. In Table 3 below, the weights are mentioned that are extracted from the WSBM.

Table 3. Derived weights of all the indicators from the DEA

INDICATORS	WEIGHT	INPUT/OUTPUT
No. of Bank Branches	0.25	
No. of ATM	0.25	
No. of Bank Mitra Engaged	0.25	INPUT VARIABLE
No. of Training Program Organized	0.25	
No. of Accounts Opened By BME	0.167	
Amount Accumulated by BME	0.167	
No. of ATM Card	0.167	
Volume of Deposit	0.167	
Volume of Credit	0.167	OUTPUT VARIABLE
No. of Persons Trained from the Training Program	0.167	

Source*: Author's Calculation*

4.3 Financial Inclusion Index/Efficiency Score Through Data Envelopment Analysis

Table 4 shows the result of the first stage of the objective, where we used the weights derived by performing the weighted slack-based measure of DEA to calculate the efficiency score. The extracted weights are assigned to the linear equation discussed above in section 3.2.1. In the case of calculating the efficiency score from data envelopment analysis, all the efficient districts scored one, and inefficient districts scores less than one. 27 districts score one and efficient for the year 2020-2021. The other 11 districts are inefficient scoring less than one. The lowest score is obtained by the district Sheikhpura with a value of 0.2727 and ranks 38 among all. If the various DMUs are efficient, their efficiency value in the basic model is "1," making it difficult to identify their efficiency. Consequently, the efficiency of the DMUs cannot be properly assessed, and the basic DEA model can only determine whether a DMU is efficient or inefficient. In the SE-DEA (super-efficient) model, a performing DMU is capable of raising its input proportionally while sustaining its effective efficiency (Li et al., 2021). According to (Andersen & Petersen, 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.

4.4 Financial Inclusion Index Through UNDP Approach Using the Weights Derived From DEA

Considering the two commonly used approaches to measure financial inclusion through the non-parametric method (UNDP approach) and the parametric method represented by the PCA method. We have performed another non-parametric technique to extract the weights of all the indicators that are derived from the data and are free from choosing the weights exogenously based on researchers' intuition. The correct assignment of weights is important methodologically since a slight change in weights can alter the results dramatically (Lockwood, 2004).

In line with Goel and Sharma (2017), IFI is classified into three categories high, medium, and low. By this classification, nineteen out of 38 districts are classified as high IFI districts. The highest score is obtained by Patna with a value of 0.940. The medium IFI districts are sixteen. Three out of thirty-eight come under the low financial inclusion index. There is variation seen in the score from both methods. Through DEA, the lowest score is obtained by Sheikhpura, and through the UNDP approach the lowest score is obtained by Arwal with a value of 0.377.

Table 4. Financial inclusion efficiency score through DEA, where weights are derived from the WSBM model of DEA

S.NO	DISTRICTS	SCORE	RANK
1	Araria	1	1
2	Arwal	1	1
3	Aurangabad	1	1
4	Banka	0.3984	36
5	Begusarai	0.4144	35
6	Bhagalpur	0.2863	37
7	Bhojpur	0.4796	33
8	Buxar	0.5677	30
9	Darbhanga	0.6362	29
10	East Champaran	1	1
11	Gaya	1	1
12	Gopalganj	1	1
13	Jamui	1	1
14	Jehanabad	0.5339	32
15	Kaimur	1	1
16	Katihar	1	1
17	Khagaria	1	1
18	Kishanganj	1	1
19	Lakhisarai	1	1
20	Madhepura	1	1
21	Madhubani	0.6502	28
22	Munger	1	1
23	Muzaffarpur	1	1
24	Nalanda	0.5527	31
25	Nawada	1	1
26	Patna	1	1
27	Purnea	1	1
28	Rohtas	1	1
29	Saharsa	1	1
30	Samastipur	0.4428	34
31	Saran	1	1
32	Sheikhpura	0.2727	38
33	Sheohar	1	1
34	Sitamarhi	1	1
35	Siwan	1	1
36	Supaul	1	1
37	Vaishali	1	1
38	West Champaran	1	1

Source: Author's Calculation

5. Conclusion and Policy Implications

FI is a matter of global concern because it brings many economic benefits to the country as a whole and people as individuals (Jaiswal et al., 2024). It helps small businesses to work on their growth and encourages the sustainable use of financial resources. It is also seen as a way to prevent social exclusion (Jaiswal et al., 2024; Kumar et al., 2025). However, there have been so many efforts to measure financial inclusion by previous authors, but these efforts have not been adequately performed. The current method of calculating the index is questionable because it chooses arbitrary weights. In addition, the factor "training program organized, and the persons participated" holds an important position in calculating the status of FI of an underdeveloped state. Therefore, the absence of these factors in the FI measurement will not accurately reflect its level.

Table 5. Financial Inclusion Index through the UNDP approach, where weights are derived from the WSBM model of DEA

S.NO	DISTRICTS	FII SCORE	RANKING
1	Araria	0.627	17
2	Arwal	0.377	38
3	Aurangabad	0.481	32
4	Banka	0.564	23
5	Begusarai	0.494	31
6	Bhagalpur	0.539	25
7	Bhojpur	0.519	28
8	Buxar	0.476	33
9	Darbhanga	0.635	15
10	East Champaran	0.720	6
11	Gaya	0.662	10
12	Gopalganj	0.600	21
13	Jamui	0.670	9
14	Jehanabad	0.419	37
15	Kaimur	0.500	30
16	Katihar	0.544	24
17	Khagaria	0.588	22
18	Kishanganj	0.602	20
19	Lakhisarai	0.435	35
20	Madhepura	0.603	19
21	Madhubani	0.662	11
22	Munger	0.429	36
23	Muzaffarpur	0.733	5
24	Nalanda	0.509	29
25	Nawada	0.461	34
26	Patna	0.940	1
27	Purnea	0.709	7
28	Rohtas	0.537	26
29	Saharsa	0.614	18
30	Samastipur	0.767	2
31	Saran	0.645	13
32	Sheikhpura	0.527	27
33	Sheohar	0.657	12
34	Sitamarhi	0.749	3
35	Siwan	0.638	14
36	Supaul	0.632	16
37	Vaishali	0.735	4
38	West Champaran	0.701	8

Source: *Author's Calculation*

By using State-level bankers committee report quarterly data (2020-2021) and using weights extracted from the weighted slack-based measure of DEA, we propose two overall financial inclusion indexes to measure the FI level of 38 districts of Bihar. This method is a good statistic for building an FI index because our FI index is a multidimensional index symbolizing both the efficiency score and inclusion index, where dimensions are maximized. It is easy to explain and calculate. It can also be compared over time to many states and countries around the globe. Moreover, when compared to other studies, it shows that our FI index not only corroborates with them but is also superior to Sarma's technique following the UNDP approach.

For academicians, this study advances financial inclusion research by using Data Envelopment Analysis (DEA) to derive data-driven weights, addressing critiques of subjective weight assignment. The replicable structure helps academicians to modify indicators for different countries or regions. New indicators such as Bank Mitra activities and training programs draw attention to context-specific factors in developing countries, so motivating researchers to investigate related proxies elsewhere. Reflecting the rise of mobile banking and fintech, future research could include digital financial inclusion or do longitudinal studies tracking financial inclusion over time. Given Demirgüç-Kunt et al. (2018) link financial access to economic empowerment, scholars should validate the index against outcomes like poverty reduction or SMEs growth.

For policymakers, the Financial Inclusion Index is a practical tool for evidence-based decisions. District classifications (e.g., Patna at 0.940, Arwal at 0.377) guide targeted interventions to boost financial inclusion. Policymakers can allocate resources to low-FI districts, enhancing banking infrastructure, Bank Mitra engagement, and financial literacy programs. Training-related indicators emphasize capacity-building for rural areas. Drawing from Kenya's mobile money success (Suri & Jack, 2016), partnerships with fintech firms could improve accessibility in Bihar. The index's comparability supports benchmarking, enabling learning from high-performing districts like Patna. Policymakers should establish monitoring systems to track progress, aligning with the Reserve Bank of India's financial inclusion goals, ensuring sustained economic and social benefits.

In conclusion, this research helps policymakers and communities see the importance of FI in the economy. From here, there is a solution to combine FI to calculate its impact levels on the other factors.

Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding information

The author declared no financial support for the research, authorship, and/or publication of this article.

Acknowledgments: None

References

Albagoury, S. H. (2021). African pathway to achieve inclusive growth: COMESA case study. *Journal of Humanities and Applied Social Science*, *3*(2), 108–119. https://doi.org/10.1108/JHASS-03-2020-0045

Ambarkhane, D., Shekhar Singh, A., & Venkataramani, B. (2016). Developing a Comprehensive Financial Inclusion Index. *Management and Labour Studies*, *41*(3), 216–235. https://doi.org/10.1177/0258042X16666579

Ambarkhane, D., Singh, A. S., Venkataramani, B., & Marak, Z. (2022). Overcoming barriers to financial inclusion: Empirical evidence from India. *International Journal of Social Economics*, *49*(9), 1302–1323. https://doi.org/10.1108/IJSE-04-2020-0254

Amidzic, G., Massara, A., & Mialou, A. (2014). Assessing Countries' Financial Inclusion Standing: A New Composite Index. In *IMF Working Papers* (Issue 36). https://doi.org/10.5089/9781475569681.001

Andersen, P., & Petersen, N. C. (1993). A Procedure for Ranking Efficient Units in Data Envelopment Analysis. *Mangement Science*, *39*(10), 1261–1264. https://doi.org/https://doi.org/10.1287/mnsc.39.10.1261

Bozkurt, I., Karakus, R., & Yildiz, M. (2018). Spatial determinants of financial inclusion over time. *Journal of International Development*, *30*(8), 1474–1504. https://doi.org/10.1002/jid.3376

Camara, N., & Tuesta, D. (2014). Measuring Financial Inclusion: A Multidimensional Index. *BBVA Research Paper*, *14/26*.

Cooper, W. W., Seiford, L. M., & Tone, K. (2006). Introduction to data envelopment analysis and its uses. In *Springer* (Vol. 59).

Cooper, W. W., Seiford, Lawrence M., & Zhu, J. (2010). Handbook on Data Envelopment Analysis. In *International Series in Operations Research & Management Science* (Vol. 164). https://doi.org/10.1007/978-1-4419-6151-8

Danquah, M., Iddrisu, A. M., Quartey, P., Ohemeng, W., & Barimah, A. (2021). Rural financial intermediation and poverty reduction in Ghana: A micro-level analysis. *Poverty & Public Policy, 13*(4), 316–334. https://doi.org/10.1002/pop4.324

Dar, A. B., & Ahmed, F. (2020). Financial inclusion determinants and impediments in India: insights from the global financial inclusion index. *Journal of Financial Economics*, 13(3), 391-408. https://doi.org/10.1108/JFEP-11-2019-0227

Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S., & Hess, J. (2018). *The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution*. World Bank. https://doi.org/10.1596/978-1-4648-1259-0

Goel, S., & Sharma, R. (2017). Developing a financial inclusion index for India. *Procedia Computer Science*, *122*, 949–956. https://doi.org/10.1016/j.procs.2017.11.459

Gupte, R., Venkataramani, B., & Gupta, D. (2012). Computation of financial inclusion index for India. *Procedia - Social and Behavioral Sciences*, *37*, 133–149. https://doi.org/10.1016/j.sbspro.2012.03.281

Jaiswal, J. K., & Pandey, D. K. (2025). Navigating the digital finance landscape amid covid-19: A bibliometric analysis. In C. E. C. Gan, N. Hewa-Wellalage, & A. I. Hunjra, *Transformations in Banking, Finance and Regulation* (Vol. 17, pp. 109–141). WORLD SCIENTIFIC (EUROPE). https://doi.org/10.1142/9781800616257_0005

Jaiswal, J. K., Kumar, B., & Kumari, P. (2024). Women empowerment through self-help groups: A systematic review and research agenda. *Journal of Management and Entrepreneurship*, *18*(2), 99–115. https://doi.org/10.70906/20241802099115

Jaiswal, J. K., Pandey, D. K., & Kumar, B. (2024). Green and sustainable finance research in BRICS countries: Review and research agenda. *Development and Sustainability in Economics and Finance*, *1*, 100008. https://doi.org/10.1016/j.dsef.2024.100008

Kodan, A. S., & Chhikara, K. S. (2011). Status of Financial Inclusion in Haryana : An Evidence of Commercial Banks. *Management and Labour Studies*, *36*(3), 247–267. https://doi.org/https://doi.org/10.1177/0258042X1103600303

Kodan, A. S., & Chhikara, K. S. (2013). A Theoretical and Quantitative Analysis of Financial Inclusion and Economic Growth. *Management and Labour Studies*, *38*(1–2), 103–133. https://doi.org/10.1177/0258042X13498009

Kumar, B., Mahato, J., Pandey, D. K., & Jaiswal, J. K. (2025). Elevating rural womens empowerment: A case study on the impact of the sustainable livelihood scheme on extreme poverty in Bihar, India. *International Journal of Entrepreneurship and Small Business*, *1*(1), 10065972. https://doi.org/10.1504/IJESB.2025.10065972

Kumari, P., & Jaiswal, J. K. (2024). Sustainability and finance in developing nations: Current state and future directions. *International Journal of Accounting, Business and Finance*, *2*(2), 40–62. https://doi.org/10.55429/ijabf.v2i2.119

Kushwaha, A., Kumar, B., & Jaiswal, J. (2023a). Enhancing financial inclusion in bihar through efficient resource allocation: A slack-based dea framework. *Scope*, *13*, 911.

Kushwaha, A., Kumar, B., & Jaiswal, J. (2023b). *Unlocking bihar's financial potential exploring the efficiency of financial inclusion with data envelopment analysis*. *XVII*, 90–116.

Li, L. L., Seo, Y. J., & Ha, M. H. (2021). The efficiency of major container terminals in China: super-efficiency data envelopment analysis approach. *Maritime Business Review*, *6*(2), 173–187. https://doi.org/10.1108/MABR-08-2020-0051

Lockwood, B. (2004). How robust is the Kearney/foreign policy globalization index? *World Economy*, *27*(4), 507–523. https://doi.org/10.1111/j.0378-5920.2004.00611.x

Luo, D., Luo, M., & Lv, J. (2022). Can Digital Finance Contribute to the Promotion of Financial Sustainability? A Financial Efficiency Perspective. *Sustainability*, *14*(7). https://doi.org/10.3390/su14073979

Mahadeva, M. (2008). Financial Growth in India: Whither Financial Inclusion? *Margin- The Journal of Applied Economic Research*, *2*(2), 177–197. https://doi.org/10.1177/097380100800200202

Maity, S., & Sahu, T. N. (2020). Role of public sector banks towards financial inclusion during pre and post-introduction of PMJDY: a study on efficiency review. *Rajagiri Management Journal*, *14*(2), 95–105. https://doi.org/10.1108/ramj-03-2020-0009

Nguyen, T. T. H. (2020). Measuring financial inclusion: a composite FI index for the developing countries. *Journal of Economics and Development*, *23*(1), 77–99. https://doi.org/10.1108/JED-03-2020-0027

Pandey, D. K., Kumar, B., Elommal, N., & Jaiswal, J. K. (2025). Navigating social regulations during crises: A comprehensive bibliometric and systematic literature review. *International Journal of Business and Emerging Markets*, *1*(1), 10064229. https://doi.org/10.1504/IJBEM.2025.10064229

Ramanathan, & R. (2003). An introduction to data envelopment analysis. In *Sage Publications*.

Sarma, M. (2008). Index of Financial Inclusion. *Indian Council for Research on International Economic Relations*, *215*.

Sarma, M., & Pais, J. (2008). *Financial Inclusion and Development: A Cross Country Analysis* (Issue 4).

Sarma, M., & Pais, J. (2011). Financial Inclusion and Development. *Journal of International Development*, *23*, 613–628. https://doi.org/10.1002/jid.1698

Sethy, S. K. (2016). Developing a Financial Inclusion Index and Inclusive Growth in India. *Theoretical and Applied Economics*, *23*(2), 187–206. https://doi.org/10.1177/0019466220150210

Shafi, M., & Medabesh, A. H. (2012). Financial Inclusion in Developing Countries: Evidence from an Indian State. *International Business Research*, *5*(8), 116–122. https://doi.org/10.5539/ibr.v5n8p116

Sharma, D. (2016). Nexus between financial inclusion and economic growth Evidence from the emerging Indian economy. *Journal of Financial Economic Policy*, *8*(1), 13–36. https://doi.org/10.1108/JFEP-01-2015-0004

Siddiqui, T. A., & Siddiqui, K. I. (2020a). FinTech in India: An analysis on impact of telecommunication on financial inclusion. *Strategic Change*, *29*(3), 321–330. https://doi.org/10.1002/jsc.2331

Siddiqui, T. A., & Siddiqui, K. I. (2020b). Telecommunication, socioeconomic, and financial inclusion: An empirical evidence from Bihar. *Prabandhan: Indian Journal of Management*, *13*(10–11), 46. https://doi.org/10.17010/pijom/2020/v13i10-11/156008

Suri, T., & Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science, 354*(6317), 1288–1292. https://doi.org/10.1126/science.aah5309

Tram, T. X. H., Lai, T. D., & Nguyen, T. T. H. (2021). Constructing a composite financial inclusion index for developing economies. *The Quarterly Review of Economics and Finance*. https://doi.org/10.1016/j.qref.2021.01.003

Xia, Y., & Xu, G. (2025). Can digital financial inclusion promote the sustainable growth of farmers' income? — An empirical analysis based on panel data from 30 provinces in China. *Sustainability, 17*(4), 1448. https://doi.org/10.3390/su17041448

Yadav, P., & Sharma, A. K. (2016). Financial Inclusion in India: an application of TOPSIS. *Humanomics*, *32*(3). https://doi.org/http://dx.doi.org/10.1108/H-09-2015-0061

Yadav, V., Singh, B. P., & Velan, N. (2021). Multidimensional financial inclusion index for Indian states. *Journal of Public Affairs*, *21*(3). https://doi.org/10.1002/pa.2238

Zhu, S., Kavanagh, E., & Sullivan, N. O. (2021). Constructing a financial conditions index for the United Kingdom: A comparative analysis. *International Journal of Financial Economics*, *26*(2), 2976–2989. https://doi.org/10.1002/ijfe.1945

Zulaica Piñeyro, C. M. (2013). Financial Inclusion Index: Proposal of a Multidimensional Measure for Mexico. *Revista Mexicana de Economía y Finanzas*, *8*(2), 157–180. https://doi.org/10.21919/remef.v8i2.46