Journal of Marketing & Social Research

ISSN (Online): 3008-0711

Volume: 02 | Issue 03 | Apr-May. | 2025
Journal homepage: https://jmsr-online.com/

Research Article

Efficiency Analysis of Microfinance Institutions of South Asia: A DEA Analysis

Samreen Farooq[1] and Prof. S.M. Jawed Akhtar[2]
[1]Research Scholar, Department of Economics, Aligarh Muslim University
[2]Professor, Department of Economics, Aligarh Muslim University

Submission: 20/02/2025; Received: 23/03/2025; Revision: 26/04/2025; Published: 09/05/2025

***Corresponding author:** Samreen Farooq (samreenfarooq92@gmail.com)

Abstract: Microfinance is the most widely used method for achieving financial inclusion and giving unbanked people steady and dependable financial support. Thus, microfinance institutions seek to strike a balance between their financial objectives and their social impact. Microfinance institutions need to operate more efficiently to meet these objectives. Using the Data Envelopment Analysis Model, we estimated two different types of efficiencies (financial and social) for 74 Microfinance Institutions in South Asia from 2010 to 2018. The empirical findings support the notion that, throughout the study period, South Asian microfinance institutions were more financially than socially efficient. In addition, Indian microfinance institutions are outperforming their peer nation counterparts regarding social outreach and financial sustainability. The lowest-performing microfinance institutions were discovered to be those in Pakistan.

Keywords: Microfinance, South Asia, Financial Efficiency, Social Efficiency, Data Envelopment Analysis, Bootstrap Data Envelopment Analysis.

INTRODUCTION

Microfinance was first introduced in Bangladesh and has been practiced in South Asia for about forty years. While microfinance has historically helped both developing and rich nations, South Asia has seen a surge in the popularity of microfinance institutions in the last ten years. (Seibel,2013). Prof. Muhammad Yunus, a banking inventor from Bangladesh who shared the 2006 Nobel Peace Prize with Grameen Bank, devised this strategy. Microfinance is one of the most popular strategies employed now in South Asian countries to combat poverty. Offering banking services to the underprivileged who do not use the standard banking system is the primary goal of Microfinance Institutions. The most significant characteristic that sets microfinance institutions apart from regular banks is their twin purpose of balancing financial aims with social impact and their primary goal of providing banking facilities.

Microfinance Institutions are unique financial entities that aim to achieve sustainability and welfare simultaneously (Bassem, 2014). The institutionalist and welfarist paradigms are the two underlying concepts that these two goals center upon. While the welfarist paradigm adheres to the goal of reducing poverty and expanding outreach, the institutionalist paradigm pushes MFIs to generate enough revenue to meet operational and financial costs (Olasupo,2014). Thus, MFIs have social or development goals in addition to financial goals. Evaluating microfinance organizations' performance requires taking into consideration both goals. The first has to do with the industry's financial viability, while the second is about its influence on society. The capacity of an organization to expand its operations to a large number of clients and pay for all of its expenses is known as financial efficiency. The concept of social performance is multifaceted; therefore, evaluating it is more intricate and comprehensive. The Social Performance Task Force (SPTF) group states that social performance is "the effective implementation of an institution's social mission into practice." This goal could involve helping many underprivileged and marginalized individuals, providing appropriate and high-quality financial services, benefiting clients, and enhancing the Microfinance Institutions' social responsibility. (CGAP,2007).

The microfinance industry has seen several notable changes in the last 20 years. One of these changes was the industry's commercialization, which led to the institutional transformation of some MFIs from socially conscious non-profit organizations to for-profit organizations (Fernando,2004). Donors and social investors may view the social efficiency of microfinance as a crucial criterion to evaluate MFIs before contributing, as commercialization is linked to the phenomenon known as the "microfinance mission drift" (Fall et al.,2021). While MFIs prioritize financial sustainability (Hardy et al., 2003), social performance is given greater weight by the authorities who grant funding than financial performance (Weiss & Montgomery, 2005).

In the banking sector, efficiency research is rather prevalent. Such work is more modern and incorporates new elements in microfinance. Due to the perceived increased attention that microfinance has received over time, it is imperative to examine the efficiency of this sector. When analyzing efficiency, it is necessary to consider the dual purpose of microfinance. Specifically, social efficiency must be considered in addition to financial efficiency. An MFI is considered efficient if it either maximizes its revenue and outreach or minimizes its production costs. Therefore, outreach is utilized to assess the program's social efficiency, whereas technical and allocative efficiency adds to an MFI's economic or financial efficiency.

Two primary methods exist for assessing efficiency in general and microfinance in particular: parametric and non-parametric methodologies. The former is split into two categories: stochastic techniques and deterministic parametric approaches, and it is based on an econometric estimate of the efficiency frontier. Deterministic approaches risk being prejudiced since, in their case, any deviation from the frontier is attributed to inefficiency. This is especially true when measurement errors are present in the data. Alternatively, one can use stochastic frontier methods, the most well-known of which is Stochastic Frontier Analysis (SFA). Its primary benefit is that it can distinguish between the inefficiency caused by random shocks and the inefficiency caused by the firm's technological inefficiencies.

On the other hand, non-parametric techniques do not need the functional form to be specified. The mathematical approximation of a linear programming function that links inputs and outputs serves as its foundation. The Data Envelopment Analysis (DEA) and the Free Disposal Hull (FDH) are the primary methodologies that stand out in this group. DEA is the most common type of research in microfinance.

LITERATURE REVIEW

Pellegrina L.D. et al. (2024) used DEA and Regression analysis to investigate how well 38 European MFIs balanced their social and financial sustainability objectives. According to the study's findings, MFIs with strong social outcomes are also financially viable. The authors also conclude that European MFIs rely more on legislation and subsidies that are not suitable for the microfinance industry. Blanco-Oliver A.J.et al. (2023) examine the linear and non-linear effects of loan size on the financial and social efficiencies of MFIs. The authors compiled data on MFIs from 90 nations and divided it into six geographical areas. The analysis in the paper is two-staged. First, an input-oriented DEA model with constant and variable returns to scale was used to estimate the MFI efficiency scores. The authors also employ truncated regression. A non-linear U-shaped relationship between the loan size and MFIs' social efficiency has been observed. In contrast, a U-shaped relationship has been found between the loan size and MFIs' financial efficiency. Bardhan A.K. et al. (2023) also employed a two-step methodology to assess the financial and social effectiveness of Indian MFIs. In step one, bias-corrected bootstrap DEA efficiency scores for social and financial efficiency were computed using two input and two output variables. In the subsequent phase, the efficiency scores serve as the dependent variable, and the SUR (Seemingly Unrelated Regression Model) is utilized to determine the factors that influence the financial and social effectiveness of microfinance institutions in India. The study concludes that Indian MFIs' overall financial efficiency is higher than their social efficiency. The findings of SUR indicate that non-NBFC MFIs have higher financial and social efficiency levels than NBFC MFIs. Murdiati E. et al. (2023) used DEA and Multivariate Panel Regression Analysis to examine how the culture of women borrowers affected the financial efficiency of 90 MFIs from ASEAN-4 nations. According to the findings, ASEAN 4's greatest financial efficiency score is comparable to Cambodia's. Furthermore, a positive correlation exists between the effectiveness of MFIs and the culture of women borrowers. Khan A. et al. (2023) examine the dual goal of MFIs operating in South Asia. Using Bootstrap DEA, the authors examined the MFIs operating in four chosen SAARC nations between 2005 and 2018. The findings indicate that MFIs in South Asia skew more toward social outreach than financial stability. Furthermore, the primary reason for the poorer performance of MFIs in South Asia is managerial inefficiency. Ahmad S. et al. (2023) investigate the effects of intellectual capital and its constituent parts on MFIs in 86 countries using DEA and a truncated regression model. The study concludes that while MFIs with high intellectual capital (IC) can be more financially efficient, they are more efficient financially than socially. Additionally, IC significantly improves the effectiveness of social outreach. Using a DEA-based meta-frontier methodology, Widiarto and Emrouznejad (2015) evaluated the effectiveness of 231 Islamic and conventional MFIs operating in the MENA, East Asia-Pacific, and South Asia areas during the 2009–2010 fiscal year. The findings verified that conventional microfinance institutions performed superior in the MENA region. Islamic MFIs were to be more socially responsible, though. Wijesiri et al. (2015) employed a two-staged double bootstrap approach to examine the dual goals of microfinance in 36 MFIs in Sri Lanka. The efficiency scores obtained in the first stage are used as the dependent variable in the second stage. According to the first stage's results, no MFI is efficient financially and socially. MFIs that were thought to be efficient based on their original efficiency scores became less efficient when using the bias-corrected approach. The results of the second-stage regression indicate that financial and social efficiency factors differ. Gutierrez-Nieto et al. (2007) employed the DEA model to examine the efficiency of microfinance in 30 Latin American MFIs using different combinations of inputs and outputs. They concluded that the efficiency level depends upon the input-output specification used in the DEA model.

DATA AND METHODOLOGY

THE MODEL

DEA is a non-parametric technique used to determine the efficient production frontier and evaluate the relative efficiency of Decision-Making Units (DMUs), which are responsible for converting inputs into outputs. In DEA terminology, an economic unit is referred to as a ‘Decision Making Unit’ (DMU). Data Envelopment Analysis (DEA) is a non-parametric method that investigates the sensitivity of the efficiency scores measured by DMUs. (Simar & Wilson,2007). Data Envelopment Analysis (DEA) is a widely used mathematical programming technique for assessing the relative efficiency of a group of homogenous DMUs that employ the same inputs (in varying amounts) to generate the same outputs (in different quantities). (Benitez et al., 2021). Using operations research's linear programming technology, the DEA approach examines the envelope surface of input and output data from various decision-making units. (Quing Guan et al.,2022). Charnes, Cooper, and Rhodes first put forth the original DEA model, thus known as the CCR model (Charnes et al., 1978). It assumes that the technology exhibits constant returns to scale (CRS). Since the constant returns to scale assumption aren't necessarily true, this assumption can be relaxed by incorporating the so-called convexity restriction (Banker et al., 1984). As a result, the resulting model, sometimes referred to as the Banker, Charnes, and Cooper's DEA model or BCC model, permits the efficient frontier to display variable returns to scale (VRS).

DEA does not allow for random error and takes into account multiple dimensions of organizational performance. Stated differently, the distance between the observation and the efficient boundary is assumed by DEA to indicate only inefficiency. However, measurement error may affect the input-output levels, representing both inefficiency and noise. Recent DEA literature allows us to correct it. To address bias in DEA estimators and construct confidence intervals for those indices, Simar and Wilson (1998) specifically suggested using the bootstrapping technique. By resampling and applying the original estimator to each simulated sample, bootstrapping repeatedly simulates the process of generating data and produces estimates that closely resemble the estimators of interest's original, unknown sampling distribution.

Two methods are used in the basic DEA model: output-oriented and input-oriented. In the input-oriented model, the inputs are proportionately minimized, keeping the output constant, while in the output-oriented model, the output is proportionally maximized, keeping the inputs constant. Equation 1 and Equation 2 below explain input-oriented and output-oriented models, respectively.

$$\theta = Min\,\theta$$

Subject to

$$\sum_{j=1}^{n} \lambda_j Y_{rj} \geq Y_{ro} \qquad r = 1,2,\ldots\ldots s;$$
$$\sum_{j=1}^{n} \lambda_j X_{ij} \leq \theta X_{io}, \qquad i = 1,2,\ldots\ldots, m;$$
$$\sum_{j=1}^{n} \lambda_j = 1 \qquad \text{(eq 1)}$$
$$\lambda_j \geq 0, \qquad j = 1,2,\ldots\ldots, n.$$

$$\emptyset = Max\,\emptyset$$

Subject to

$$\sum_{j=1}^{n} \lambda_j Y_{rj} \geq \emptyset Y_{r0} \qquad r = 1,2,\ldots\ldots, s;$$
$$\sum_{j=1}^{n} \lambda_j X_{ij} \leq X_{i0}, \qquad i = 1,2,\ldots\ldots m;$$
$$\sum_{j=1}^{n} \lambda_j = 1 \qquad \text{(eq 2)}$$
$$\lambda_j \geq 0 \qquad j = 1,2,\ldots\ldots, n.$$

The input-oriented model seeks to minimize the MFIs' inputs proportionately while maintaining their existing output level. Applying this procedure to every MFI results in an efficiency score for the MFI, where $\theta = 1$ denotes an efficient MFI, and $\theta < 1$ is an inefficient MFI. The model is established as VRS when $\theta = 1$. The input-oriented and output-oriented DEA models are nearly identical in that they both define technical efficiency (TE) $\emptyset$ ratings ranging from zero to one.

When a DMU's performance is compared to other DMUs, and it cannot be established that some of its inputs or outputs can be enhanced without making others worse, the DMU is considered fully efficient (Cooper,2013). The selection of prospective factors to be considered in a DEA model is crucial. Generally speaking, when a DMU uses a resource to produce goods or services, that resource should be considered an input variable, and the outputs come from the activity and performance metrics. (Wang,2021). Researchers have proposed a general rule of thumb regarding the relationship between the number of observations and the number of inputs and outputs. (Bogetoft & Otto,2011). The rule suggests that the number of firms, indicated by 'n,' should exceed 3 times the number of inputs and outputs [$n > 3\ (p + q)$] and should be greater than the product of the number of inputs and the number of outputs ($n > pq$). (Cooper et al., 2007)

BOOTSTRAP DEA PROCEDURE

We use the bootstrap technique, which repeatedly simulates the data-generated process to generate new estimates with each simulation (Efron,1997; Efron & Tibshirani, 1993). Moreover, the bootstrapped confidence intervals can be obtained from the distribution of resampled estimates to verify if efficiency estimates are statistically significant (Fuentes,2011). To determine the data set's confidence intervals, we employed 2,000 bootstrap samples, as per Simar and Wilson (2007).

METHODOLOGY

We employed Simar and Wilson's (1998, 2000) homogeneous bootstrap approach in the Data Envelopment Analysis (DEA) Model. The efficiency of the bootstrap DEA models is valid and dependable when the sample size is small. In the current work, we used an output-oriented model for social efficiency and an input-oriented model for financial efficiency.

DATA

Secondary data taken from MixMarket (http://www.themix.org) was used in the study. The four SAARC nations—Bangladesh, India, Nepal, and Pakistan—that we have chosen are included in our analysis because the data is not available for the rest of the countries, i.e., Afghanistan, Bhutan, the Maldives, and Sri Lanka. We have used the data for nine years, i.e., from 2010 to 2018.

INPUT-OUTPUT SELECTION

In our study, we measure financial and social efficiency based on the dual goals of MFIs. We have incorporated two models in our research based on the two-fold objectives of MFIs. For financial efficiency, we employed an output-oriented model and an input-oriented approach for social efficiency. While an output-oriented model predicts a proportionate rise in output production with constant input levels, an input-oriented model assumes a proportionate reduction in input utilization. According to Marakkath (2014), output orientation is inappropriate for microfinance because maximizing outputs like interest rates and profit margins could lead to client abuse. However, we are using the number of active female borrowers as an output for social efficiency, so an output-oriented model to maximize social efficiency is considered more appropriate.

In model A, which is input-oriented, we measure the financial efficiency of MFIs. We choose a combination of three inputs and two outputs. The inputs are Total Assets, Operating Expenses, and the Number of Personnel, and the outputs used are Financial Revenue and Gross Loan Portfolio. We are measuring the financial efficiency of MFIs by incorporating GLP, which tells how efficiently the industry is placing credit, and financial revenue, which tells about how efficiently the revenue is collected.

In model B, which is output-oriented, we measure the social efficiency of MFIs. The inputs will be the same as Model A, while the output will be the number of Active Female Borrowers. Most of the studies (Widiarto and Emrouznejad, 2015; Wijesiri and Meoli, 2015; Khan and Gulathi,2019) have used the number of active borrowers as a proxy to estimate the social performance, but we rely on the number of active women borrowers since we are trying to estimate the depth of outreach (Schreiner,2002).

DEFINITION OF VARIABLES USED

Table 1: Definition of the Variables Used

Variable Name	Definition
Total Assets	The total value of resources controlled by the financial institution as a result of past events and from which future economic benefits are expected to flow to the financial institution.
Operating Expenses	Includes expenses not related to financial and credit loss impairment, such as personnel expenses, depreciation, amortization, and administrative expenses.
Gross Loan Portfolio	All outstanding principals are due for all outstanding client loans. This includes current, delinquent, and renegotiated loans, but not loans that have been written off.
Financial Revenue	This includes all financial income and other operating revenue generated from non-financial services.
No. of Active Female Borrowers	The number of individuals who currently have an outstanding loan balance with the financial institution or are primarily responsible for repaying any portion of the gross loan portfolio. (Gender, Female)
No. of Personnel	The number of individuals who are actively employed by an entity.

Source: Variable Definitions have been taken from MixMarket

DATA AVAILABLE FOR THE NUMBER OF MFIS

Table 2: Total Number of MFIs from each Country used in the Study

Country	No of MFIs
Bangladesh	17
India	31
Nepal	8
Pakistan	18
Total	74

EMPIRICAL RESULTS

The most essential characteristic of microfinance is its ability to balance the financial goal with the social agenda. The MFIs aim to empower women and poor people while balancing the financial sustainability to operate in the long run. Therefore, the MFIs combine the social development mission with financial goals that push the institution toward self-sufficiency.

FINANCIAL EFFICIENCY

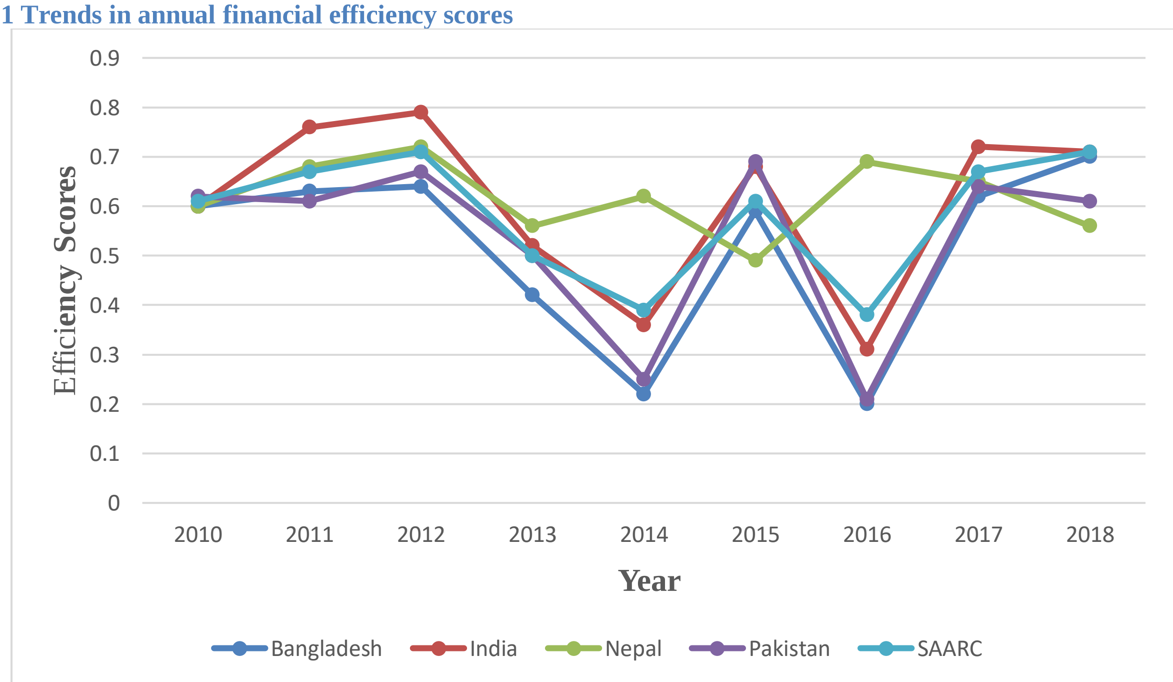
Using the input-output specification specified for Model A, we computed the efficiency scores of each MFI in the South Asia region from 2010 to 2018 to measure the financial efficiency performance of MFIs. The estimated results are reported in the table below. θ column represents the overall efficiency scores for each country in a given year. LB and UB columns provide a range for the efficiency scores, indicating the variability or uncertainty in the measurements. The LB and UB values help account for potential measurement errors or variations in the data. The selected countries' varying levels of efficiency during the study period reflect their ineffective resource allocation. This variation in the efficiency level of MFIs was also confirmed by Bibi et al. (2018). The overall average efficiency of selected SAARC countries has increased from 0.61 in 2010 to 0.71 in 2018. The efficiency of Bangladeshi MFIs has risen from 0.60 to 0.70 over the study period, and the country's average efficiency is 0.51. Indian MFIs outperformed the selected countries. The average efficiency of India's MFIs is 0.61, the highest among the selected SAARC countries. Pakistan has the lowest efficiency at 0.53, which allows for a 47% improvement. The overall average efficiency score of the SAARC region for the study period as a whole is 0.58, with a 42% allowance for improvement. The results confirm that Indian MFIs are doing financially well compared to their peer countries in the area, but there is still potential for growth. The prevalent government interventions in the region limit the expansion of the microfinance industry, even though it has greatly improved over time.

Table 3 Summary of Financial Efficiency Scores (Annual and Average)

Year/Country	**Bangladesh**			**India**			**Nepal**			**Pakistan**			**SAARC**
	θ	**LB**	**UB**	**θ**	**LB**	**UB**	**θ**	**LB**	**UB**	**θ**	**LB**	**UB**	**θ**
2010	0.60	0.58	0.62	0.60	0.54	0.67	0.60	0.54	0.64	0.62	0.56	0.68	0.61
2011	0.63	0.60	0.65	0.76	0.69	0.82	0.68	0.62	0.73	0.61	0.57	0.65	0.67
2012	0.64	0.62	0.66	0.79	0.74	0.85	0.72	0.68	0.76	0.67	0.63	0.70	0.71
2013	0.42	0.37	0.45	0.52	0.46	0.62	0.56	0.49	0.62	0.50	0.44	0.56	0.50
2014	0.22	0.19	0.23	0.36	0.32	0.42	0.62	0.59	0.70	0.25	0.22	0.27	0.39
2015	0.59	0.55	0.62	0.68	0.61	0.76	0.49	0.45	0.54	0.69	0.63	0.73	0.61
2016	0.20	0.18	0.21	0.31	0.27	0.36	0.69	0.67	0.76	0.21	0.19	0.23	0.38
2017	0.62	0.59	0.64	0.72	0.65	0.78	0.65	0.63	0.77	0.64	0.59	0.68	0.67
2018	0.70	0.67	0.71	0.71	0.65	0.77	0.56	0.59	0.85	0.61	0.57	0.65	0.71
Mean	0.51	0.48	0.53	0.61	0.55	0.67	0.60	0.58	0.70	0.53	0.49	0.57	0.58

Source: Author's calculation

Figure 1 Trends in annual financial efficiency scores



SOCIAL EFFICIENCY

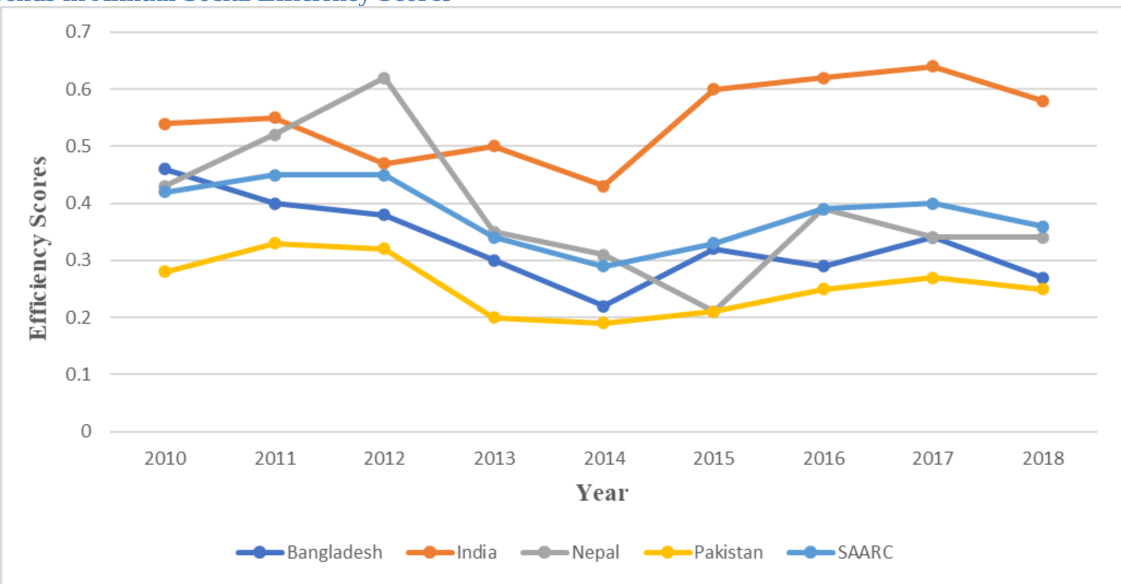
The social efficiency scores of MFIs from 2010 to 2018 were estimated using the input-output specification defined in Model B. The estimated results are reported in the Table below. ∅ column represents the overall efficiency scores for each country in a given year. LB and UB columns provide a range for the efficiency scores, indicating the variability or uncertainty in the measurements. The LB and UB values help account for potential measurement errors or variations in the data. In 2010, Bangladesh had a total efficiency score of 0.46, indicating a 54% allowance for improvement in social outreach. Pakistan has the lowest score of 0.28, while India has the highest score, i.e., 0.54, which allows a 46% improvement. Over the years, India has performed best among all the four countries. It has the highest average efficiency score of 0.46. The average efficiency score for the SAARC region is only 0.38.

Table 4 Summary of Social Efficiency Scores (Annual and Average)

Year/Country	Bangladesh			India			Nepal			Pakistan			SAARC
	Ø	LB	UB	Ø	LB	UB	Ø	LB	UB	Ø	LB	UB	Ø
2010	0.46	0.41	0.48	0.54	0.47	0.60	0.43	0.38	0.46	0.28	0.24	0.30	0.42
2011	0.40	0.29	0.53	0.55	0.50	0.55	0.52	0.44	0.67	0.33	0.31	0.36	0.45
2012	0.38	0.27	0.50	0.47	0.37	0.47	0.62	0.40	0.68	0.32	0.46	0.49	0.45
2013	0.30	0.26	0.33	0.50	0.43	0.58	0.35	0.30	0.38	0.20	0.17	0.23	0.34
2014	0.22	0.18	0.25	0.43	0.35	0.50	0.31	0.24	0.33	0.19	0.15	0.21	0.29
2015	0.32	0.28	0.33	0.60	0.53	0.67	0.21	0.18	0.24	0.21	0.19	0.22	0.33
2016	0.29	0.27	0.31	0.62	0.55	0.69	0.39	0.35	0.41	0.25	0.23	0.27	0.39
2017	0.34	0.31	0.35	0.64	0.57	0.71	0.34	0.29	0.37	0.27	0.25	0.28	0.40
2018	0.27	0.24	0.28	0.58	0.52	0.65	0.34	0.31	0.36	0.25	0.23	0.26	0.36
Mean	0.33	0.28	0.37	0.55	0.48	0.60	0.39	0.32	0.43	0.26	0.25	0.29	0.38

Source: Author's calculation

Figure 2 Trends in Annual Social Efficiency Scores



CONCLUSION

The current study used the DEA approach to examine the efficiency performance of MFIs in South Asia from 2010 to 2018. The selection of inputs and outputs is based on MFIs' twin aims, which include meeting social goals and maintaining financial sustainability. To look into the twin missions of microfinance among South Asian MFIs, two DEA models—Model A, which is financial, and Model B, which is social—were created.

Our analysis's empirical findings showed that South Asian MFIs are generally more financially efficient than socially. This illustrates how, to survive over time, the whole microfinance sector is focused on financial sustainability. Furthermore, the findings also demonstrated that Indian MFIs are performing better than any peer country in terms of financial sustainability and social outreach, with MFIs in Bangladesh and Nepal coming in second and third, respectively. Pakistani MFIs were found to be the least social performers, while Bangladeshi MFIs are not performing well financially among the four nations. Redesigning their operating strategies is necessary for MFIs that perform poorly to become more efficient. Furthermore, it was discovered that none of the 74 MFIs chosen from the South Asian region were performing at optimal levels.

Even though the microfinance sector has advanced significantly since its inception, organizational interventions restrict the industry's expansion. For MFIs to accomplish the two main objectives that led to establishing the industry in the area, its policies had to be more beneficial to borrowers. The sector needs to prosper financially, but it also needs to empower women and reduce poverty.

LIMITATIONS AND FUTURE RESEARCH PROSPECTS

Nonetheless, the study's goal was to improve the body of knowledge already available on social outreach and financial sustainability. Still, the work can be expanded upon by determining more factors influencing efficiency. To assess the social performance of MFIs, we have considered the depth of outreach (number of active female borrowers); researchers can choose to analyze the breadth of outreach instead (number of total borrowers). Furthermore, the study's sample size is constrained by time constraints and data accessibility. The study can be expanded to include more MFIs in the area.

REFERENCES

1. Ahamad, S., Al-Jaifi, H. A. A., & Ehigiamusoe, K. U. (2023). Impact of intellectual capital on microfinance institutions' efficiency: The moderating role of external governance. *Journal of the Knowledge Economy*, *14*(2), 691-717.
2. Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, *30*(9), 1078-1092.
3. Bardhan, A. K., Nag, B., & Mishra, C. S. (2023). Microfinance Institutions' Efficiency and its Determinants: Evidence from India. *South Asia Economic Journal*, *24*(2), 109-136.
4. Bassem, B. S. (2014). Total factor productivity change of MENA microfinance institutions: A Malmquist productivity index approach. *Economic Modelling*, *39*, 182-189.
5. Benítez, R., Coll-Serrano, V., & Bolós, V. J. (2021). deaR-shiny: an interactive web app for data envelopment analysis. *Sustainability*, *13*(12), 6774.
6. Bibi, U., Balli, H. O., Matthews, C. D., & Tripe, D. W. (2018). Impact of gender and governance on microfinance efficiency. *Journal of International Financial Markets, Institutions and Money*, *53*, 307-319.
7. Blanco-Oliver, A. J., Irimia-Diéguez, A. I., & Vázquez-Cueto, M. J. (2023). Is there an optimal microcredit size to maximize the social and financial efficiencies of microfinance institutions? *Research in International Business and Finance*, *65*, 101980.
8. Bogetoft, P., Otto, L., Bogetoft, P., & Otto, L. (2011). Data envelopment analysis DEA. *Benchmarking with DEA, SFA, and R*, 81-113.
9. Charitonenko, S., Campion, A., & Fernando, N. A. (2004). Commercialization of microfinance perspectives from South and Southeast Asia.
10. Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European journal of operational research*, *2*(6), 429-444.
11. Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software* (Vol. 2, p. 489). New York: Springer.
12. Cooper, L. G. (2014). The Impact of Microfinance on Female Entrepreneurs in Tanzania.
13. Dalla Pellegrina, L., Diriker, D., Landoni, P., & Moro, D. (2023). Efficiency and Outreach in the European Microfinance Sector. *University of Milan Bicocca Department of Economics, Management and Statistics Working Paper*, (515).
14. Dalla Pellegrina, L., Diriker, D., Landoni, P., Moro, D., & Wijesiri, M. (2024). Financial and social sustainability in the European microfinance sector. *Small Business Economics*, 1-44.
15. Efron, B., & Tibshirani, R. (1997). Improvements on cross-validation: the 632+ bootstrap method. *Journal of the American Statistical Association*, *92*(438), 548-560.
16. Efron, B., & Tibshirani, R. J. (1993). Estimates of bias. In *An introduction to the bootstrap* (pp. 124-140). Springer US.
17. Fall, F. S., Tchuigoua, H. T., Vanhems, A., & Simar, L. (2021). Gender effect on microfinance social efficiency: A robust nonparametric approach. *European Journal of Operational Research*, *295*(2), 744-757.
18. Fuentes, R. (2011). Efficiency of travel agencies: A case study of Alicante, Spain. *Tourism Management*, *32*(1), 75-87.
19. Guan, Q., Zou, S., Liu, H., & Chen, Q. (2022). Performance Evaluation Method of Public Administration Department Based on Improved DEA Algorithm. *Computational Intelligence and Neuroscience*, *2022*.
20. Gutiérrez-Nieto, B., Serrano-Cinca, C., & Molinero, C. M. (2007). Microfinance institutions and efficiency. *Omega*, *35*(2), 131-142.
21. Hardy, D., Holden, P., & Prokopenko, V. (2003). Microfinance institutions and public policy. *Policy Reform*, *6*(3), 147-158.
22. Khan, A., & Gulati, R. (2019). Assessment of efficiency and ranking of microfinance institutions in India: a two-stage bootstrap DEA analysis. *International Journal of Business Forecasting and Marketing Intelligence*, *5*(1), 23-55.
23. Khan, A., Goswami, A., & Choudhury, T. (2023). Technology gaps, social outreach and financial sustainability of South Asian MFIs: bootstrap DEA meta-frontier approach. *Electronic Commerce Research*, 1-30.
24. Marakkath, N. (2013). *Sustainability of Indian microfinance institutions: A mixed methods approach*. Springer Science & Business Media.

25. Murdiati, E., Zainal, N., Syarifudin, A., Sanusi, Z. M., & Rodzi, Z. M. (2023). Impact of Women Borrowers' Culture on the Financial Efficiency of Microfinance Institutions in ASEAN-4 Countries. *Journal of Intercultural Communication*, *23*(2), 25-32.

26. Olasupo, M. A., Afolami, C. A., & Shittu, A. M. (2014). Outreach and financial sustainability of microfinance banks in Southwest Nigeria. *International Journal of Economics and Finance*, *6*(2), 25-39.

27. Schreiner, M. (2002). Aspects of outreach: A framework for discussion of the social benefits of microfinance. *Journal of International Development*, *14*(5), 591-603.

28. Seibel, H. D. (2013). 3 Old and new worlds of microfinance in Europe and Asia. In *Southeast Asia's Credit Revolution* (pp. 40-57). Routledge.

29. Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*(1), 31-64.

30. Simar, L., & Wilson, P. W. (1998). *Productivity growth in industrialized countries* (No. UCL-Université Catholique de Louvain). Leuven: Université Catholique de Louvain.

31. Wang, C. N., Nguyen, H. P., & Chang, C. W. (2021). Environmental efficiency evaluation in the top Asian economies: an application of DEA. *Mathematics*, *9*(8), 889.

32. Weiss, J., & Montgomery, H. (2005). Great expectations: microfinance and poverty reduction in Asia and Latin America. *Oxford Development Studies*, *33*(3-4), 391-416.

33. Widiarto, I., & Emrouznejad, A. (2015). Social and financial efficiency of Islamic microfinance institutions: A Data Envelopment Analysis application. *Socio-Economic Planning Sciences*, *50*, 1-17.

34. Wijesiri, M., & Meoli, M. (2015). Productivity change of microfinance institutions in Kenya: A bootstrap Malmquist approach. *Journal of Retailing and Consumer Services*, *25*, 115-121.

35. Wijesiri, M., Viganò, L., & Meoli, M. (2015). Efficiency of microfinance institutions in Sri Lanka: a two-stage double bootstrap DEA approach. *Economic Modelling*, *47*, 74-83.